Journal of Economic Behavior and Organization 213 (2023) 193–214

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Ancestral diversity and performance: Evidence from football data

Michel Beine, Silvia Peracchi [1], Skerdilajda Zanaj [*]

Department of Economics and Management, University of Luxembourg, 6 Rue Richard Coudenhove-Kalergi, 1359, Luxembourg, Luxembourg

ARTICLE INFO

Dataset link: https://github.com/Sil-Per/Diversity_Performance_Replication_data

Keywords:
Ancestral diversity
Football
Sports team
Performance
Family names
Migration

ABSTRACT

The theoretical impact of diversity on performance is ambiguous since it leads to costs and benefits at the collective level. In this paper, we empirically assess the connection between ancestral diversity and the performance of sports teams. Focusing on football (soccer), we built a novel dataset of national teams of European countries that have participated in the European and World Championships since 1970. The ancestral diversity of national teams is measured from genetic distance scores within the team, based on information on every player's origins. Origins are recovered using a matching algorithm based on family names. Performance is measured at the match level. Identification of the causal link relies on an instrumental variable strategy based on past immigration at the country level about one generation before the competition. Our findings indicate a positive causal link between ancestral diversity and national teams' performance. We find that a one-standard increase in diversity leads to a significant increase in the goal difference of 0.77 to 1.79 goals per match (about a 1.30 goal difference per match).

1. Introduction

Over the last decades, international human mobility has increased, involving millions of people moving to other countries. Today, more than 240 million people live in a country other than where they were born. This process has led to significant changes in the cultural landscapes of the host countries, with significant consequences for the size and composition of their labor force. Migrants bring deep-seated social values, human capital, institutions, history, and traditions. Consequently, countries that have experienced significant immigration flows in the past are characterized today by greater diversity in their populations.

National teams in international sports competitions also reflect the increased diversity brought by immigration. In football, the most popular sport worldwide, national teams in immigration countries have become more diverse because the teams attract players from the more extensive and diversified talent pool available in the country. At the 2018 FIFA Men's World Cup in Russia, 84 football players competed for national teams of countries other than their country of birth. It was the second-highest absolute number of foreign-born footballers in the World Cup (van Campenhout et al., 2019). More significantly, a high proportion of players on national teams are second-generation migrants, bringing endowments different from those found in the native population of the country they play for.

Ethnic identity is a crucial dimension of diversity, potentially affecting productivity and collective performance. Pioneering work on ethnic diversity suggests that higher diversity positively affects global productivity (see Ashraf and Galor, 2013; Alesina et al., 2016a). Regarding the inherited aspect of this dimension, Ashraf and Galor (2013) focus on genetic diversity and argue that there

* Corresponding author.
E-mail addresses: michel.beine@uni.lu (M. Beine), silvia.peracchi@uni.lu (S. Peracchi), skerdilajda.zanaj@uni.lu (S. Zanaj).
[1] Current address silvia.peracchi@liser.lu.

https://doi.org/10.1016/j.jebo.2023.07.024
Received 7 November 2022; Received in revised form 13 July 2023; Accepted 15 July 2023

Available online 26 July 2023
0167-2681/

is an optimal level of diversity for productivity. On the one hand, diversity brings complementarity in skills, which results in higher productivity. On the other hand genetic diversity is associated with social non-cohesiveness, which reduces productivity. Importantly, these features are transmitted intergenerationally (Guiso et al., 2006) and as a consequence, differences among individuals with different ancestries are related to present differences in preferences and traits (Ashraf and Galor, 2013; Galor and Ozak, 2016).

In this paper, we investigate the role of ancestral diversity in the performances of national football teams. Being the most popular sport worldwide, football is captivating to study because victories of national football teams are so important shared collective experiences that they support nation-building and crystallize national identity (Depetris-Chauvin et al., 2020). Technically, an interesting aspect of this sports activity is that performances are measured precisely and are much less subject to measurement errors than other economic activities. In addition, in football, a team's performance relies on the interaction of players who need to have very different skills depending on their position on the pitch. This aspect refers to the complementarity of the skills channel mentioned above. It is empirically unclear in football to what extent the cultural channel and the divergence-in-beliefs channel associated with higher diversity are substantial and might offset the positive effect of skill complementarity. Anecdotal evidence suggests, however, that there is some belief that diversity does affect football performance positively. In 2012, Belgium won 2–0 away over Scotland during the World Cup qualification. Commenting on this result, Scotland assistant manager Mark McGhee described the Belgian team's skill pool as follows[2]:

> They are choosing from a pool that is different from ours. They have the advantage of an African connection and can bring in real athleticism. We can hope that out of the gene pool that is East Dunbartonshire, Lanarkshire and South Ayrshire, we produce a group of players that will one day be as good as them. But they have a much broader base, and I think that is a huge advantage.

On the same lines, former U.S. President Barack Obama, in his tribute speech to commemorate Nelson Mandela's birthday in 2018, praised the diversity of the French football team, stating that

> [diversity] delivers practical benefits since it ensures that a society can draw upon the energy and skills of all... people. And if you doubt that, just ask the French football team that just won the World Cup because not all these folks look like Gauls to me...[3]

As of February 18, 2021, Belgium and France were ranked first and second worldwide, respectively, according to the World Rankings provided by the Fédération Internationale de Football Association (henceforth FIFA).[4] One of the goals of this paper is to check whether some sound statistical analysis supports these perceptions and anecdotal evidence.

To establish a causal link between the sportive teams' ancestral diversity and performance, we develop specific measures of the critical dimensions, i.e., performances and ancestral diversity of football teams. Performance data are collected at the match at the World Cup and the European championship competitions from 1970 onward. We use the goal difference as the benchmark outcome variable but show that our results are robust to alternative measures. The ancestral diversity of each team is based on the bilateral *genetic distance scores* between players. Data on genetic distance scores comes from Spolaore and Wacziarg (2009), who use data from Cavalli-Sforza et al. (1994) and quantify a genetic distance that effectively measures the time since two populations shared a common ancestor. We rely on this index of ancestral distances to capture long-term population relatedness in line with the argument by Dickens (2018) that connects ancestral distances to the complementarities associated with people dissimilarities. On the one hand, narrow ancestral distance means similar traits and ideas, thus easier communication but fewer novel ideas or traits to share. Conversely, more significant ancestral distances imply a long history of remoteness and a broader spectrum of non-overlapping but more likely novel and complementary ideas and traits to share. We follow the approach of using family names to capture the ancestral background of individuals. This approach has been adopted in fields such as patent literature or the study of intergenerational mobility.[5] Our measure of ancestral diversity at the national level suggests that diversity has changed significantly throughout the investigation, especially in countries subject to past intensive immigration.

The econometric analysis of the causal link between ancestral diversity and the performance of national teams is likely to be affected by confounding factors that can bias the estimated impact of diversity. This bias's expected direction and magnitude are difficult to grab since various confounding factors can play a role. Our identification strategy relies on an instrumental variable (IV) approach that uses the ancestral diversity of past immigration flows at the population level. More specifically, we instrument the ancestral diversity of football's national teams with a measure of ancestral diversity for the immigration stocks about one generation before (20 years). The idea is that higher diversity in immigration yesterday increases the diversity of second-generation migrants who can play for the national team of their parents' adopted country today. The strict rules of eligibility for participation on a national team in football prevent the implementation of a strategy in which national federations could manipulate diversity. This

[2] Mark Wilson, "Brilliant Belgians just incomparable insists Scotland assistant coach McGhee" Wilson (2021).

[3] France24, "In Mandela address, Obama cites French World Cup model as champs of diversity" (France24, 2018).

[4] "Men's ranking: Belgium, Royal Belgian Football Association." https://www.fifa.com/fifa-world-ranking/associations/association/BEL/men/ FIFA (2020).

[5] This surname-based idea was previously adopted in the patents literature (Kerr and Kerr, 2018) and in the study of intergenerational mobility, as in Clark (2015). An alternative predictor of player origins would be, for instance, the country of birth, as used in van Campenhout et al. (2019) for their players' diversity index. This measure would likely be a good match for players who undergo naturalization, but it would fail to capture the important contribution of second-generation immigrants. This former aspect is critical for our setting, as we focus on the vertical-transmission mechanisms related to group dynamics, focus on national teams, and base our identification strategy on previous-generation migration patterns.

lowers the concern that this instrument does not comply with the exclusion restriction. Our IV results, therefore, allow uncovering an overlooked benefit of immigration: its long-run benefit in terms of performance in collective sports.

We hypothesize and then show empirically that ancestral diversity implies significant complementarities (tactical, technical and physical) among players, affecting performance positively. It is important to note that we do not, of course, address the direct effect of genes on sports performance. In contrast, our analysis addresses the benefits and drawbacks of ancestral diversity on performance measured at a collective level. We expect ancestral diversity in sports to affect performance through various channels. Using auxiliary information, we document the existence of a complementarity channel of ancestral diversity. Teams with a higher degree of diversity exhibit higher diversity in the various forms of skills required in football, such as speed, height, and power of technical ability. We also document an indirect channel related to access to nationality regulations that facilitate the acquisition of nationality for second-generation migrants tends to boost the degree of ancestral diversity within their national team, translating into better performances over time.

We find a positive net benefit on the team's performance. A one-standard-deviation increase in diversity yields an increase of more than one goal difference in favor of the team. These findings are confirmed using an alternative unilateral setting in which the outcome variable is the team's ranking. The results are also robust to whether passive players are included or not, to alternative measures of ethnic distance, to the way bilateral performances are captured, and to the fact that hosting teams usually have an advantage in football. In addition, we control for coaching quality that could confound the identification of the causal impact of diversity. The results are also robust to the number of years that past immigration flows are expected to impact the ancestral diversity of national teams in the first stage of the IV analysis. Finally, we perform a placebo test using performances in athletics, i.e., a sport where diversity should not play any role, given that competitions do not involve collective effort. We do not find any role of ancestral diversity in explaining performances in athletics.

While our paper is clearly connected with the literature on ethnic and birthplace diversity, our analysis is also related to extensive empirical literature looking at the role of immigration in football. This literature is reviewed in the next section. Our paper deviates from the existing papers in that we focus on the performances of national teams, not on football clubs. In this context, a similar analysis at the club level would be more subject to identification issues. Through transfers of players, a club can explicitly implement a strategy boosting diversity to improve the team's performance. Given the strict rules governing the composition of national teams in football, such a strategy would hardly be possible. While some naturalization strategies have sometimes been implemented, they remain more an exception than the rule.

The paper is organized as follows. Section 2 briefly reviews the relevant literature. Section 3 describes the data used in our analysis. Section 4 introduces the empirical analysis and discusses identification issues and the main results. Section 5 exposes the robustness checks and the placebo analysis. Section 6 presents the mechanisms. Tables of the benchmark analysis are in Section 8.

2. Literature review

The economic implications of diversity have produced pervasive literature. Prior studies investigate the effects of ethnic diversity on growth (Easterly and Levine, 1997; Doomernik and Bruquetas-Callejo, 2016; Ager and Brückner, 2013), on economic prosperity (Alesina et al., 2016b), on trade (Alesina et al., 2000), on polarization (Bove and Elia, 2017), on individuals' preferences (Alesina and Ferrara, 2005), on community participation (Alesina and La Ferrara, 2000) and on the provision of public goods (Spolaore and Wacziarg, 2009). Prior studies also relate diversity to the performance of collective organizations. The seminal model of Lazear (1999) emphasizes the role of global organizations as multicultural teams. To offset the costs of cross-cultural interaction, the complementarities among different workers must, however, be substantial. Delis et al. (2017) use a panel of U.K. and U.S. firms listed on the stock market and track the ancestral diversity of the board of directors, finding positive effects on the firm's performance as measured by risk-adjusted returns and the Tobin's Q. Delis et al. (2021) apply a similar analysis to the movie industry, finding an optimal degree of ancestral diversity of actors and directors on the box office figures of attendance. In Prat (2002), the diversity of team members results in diverse decision-making processes, which brings benefits in the case of actions' submodularity. Studying working groups in a global firm setting, Earley and Mosakowski (2000) propose and document that teams effectiveness is highest at the bottom and top levels of group heterogeneity, whilst Dumas et al. (2013) document that demographically dissimilar groups tend to respond less well to corporate activities that aim at stimulating group cohesion. Focusing on the mechanisms, Miller and del Carmen Triana (2009) identify innovation and reputation as key channels in the role of racial diversity of board directors and corporate performance. Shin et al. (2012) analyze the individual-level outcomes of team diversity in the context of Chinese firms. They find that a positive link between cognitive diversity and creativity depends on individuals' beliefs about their creativity and highlight the crucial role of leadership in shaping a positive effect. In the findings of Watson et al. (1993) and Horwitz and Horwitz (2007), performance gains from diverse teams would materialize after allowing for some initial burning phase in the team formation.[6]

The literature that stresses the long-term dimension of population diversity is more recent. Ashraf and Galor (2013) is the seminal contribution that relates genetic diversity and performance, whereas Spolaore and Wacziarg (2018) establishes a link between genetic distance and development. To our knowledge, our paper is the first study to explore the effects of ancestral diversity on sports performance.

[6] As we focus on national teams, we believe that team formation is already consolidated at the moment of the performance and this mediator is less of a concern in our setting. Yet, we also include a set of team-level controls such as average age and players turnover, which would further account for possible asymmetries in team characteristics.

Our paper also relates to the literature investigating the drivers of sports performance and the sports market. Among these contributions, Bryson et al. (2013) look at the wage premia of scarce skills, focusing on two-footedness. Rodríguez et al. (2019) observes that the market values of top European players are derived mainly from their performance, presence in the national squads, age, and age squared. Fischer (2021) explore the role of COVID-19 infections on the productivity of footballers and their teammates. Kleven et al. (2013) document how taxation influences the international displacement and sorting of players in the European soccer market. Broadly related is also the contribution of Depetris-Chauvin et al. (2020), which looks at the links between football victories and expressed ethnic identity in sub-Saharan Africa.

Focusing on the dimension of diversity in sports, Kahane et al. (2013) provide evidence from hockey and generally find a positive effect of cultural diversity. Parshakov et al. (2018) use e-sport data to investigate the impact of cultural, language, and experience heterogeneity on performance. Cultural diversity correlates positively with tournament performance, while language and experience diversity affect performance negatively. Gould and Winter (2009) build a panel of baseball players from 1970 to 2003 and observe that workers' (players') efforts and interactions depend on the complementarities in the production technology. A recent contribution by Tovar (2020) explores the link between diversity, national identity, and performance at the player and team level, analyzing data from the Spanish and English leagues. The study found a non-linear relationship between the team's and the player's performance.[7] Focusing on club-level performance, Brox and Krieger (2022) provide evidence from German men's football, finding that an intermediate level of birthplace diversity maximizes team performance. Addesa et al. (2022) analyze matches from 10 Italian Serie A clubs seasons and find birthplace fractionalization to be negatively related to match-level performance. Ingersoll et al. (2017) enlarge the set of countries and investigate the effect of cultural diversity on the club teams' performances in the top leagues in the UEFA Champions League (2003–2012) for Germany, England, Italy, France, and Spain. In their findings, culturally heterogeneous teams outperform homogeneous ones, cultural diversity being proxied by linguistic diversity data based on players' nationality.

We contribute to the sports literature in various areas. We use ancestral diversity to capture deeply rooted differences in values related to culture, language, and other diversity dimensions. This measure of diversity helps to attenuate any endogeneity concern. The dataset we build for that purpose includes a much larger number of countries and tournaments than previous studies. We establish a causal link between performance and diversity, not just a correlation. Finally, our perspective is innovative as we tackle the importance of an intergenerational aspect of diversity in sports teams. In doing so, we can better assess the causality of the relationship between past immigration, diversity, and sports performance.

3. Data

To analyze the impact of ancestral diversity on the performance of national football teams, we collect and build indicators of diversity and performance, among other variables. This section explains how the critical data, namely, ancestral diversity at the team level and the performance, are built. We then present other variables that enter into the subsequent econometric analysis.

3.1. National team composition

Our crucial indicator of interest in explaining the performance of a given national football team is its ancestral diversity. To capture this relationship, we gather information on players' team composition and ethnicity. Then the individual information on the player's origins is combined to indicate the team's diversity.

We collect data on the composition of national squads from the website *worldfootball.net*, with some comparisons and checks using *soccerway.com* and Wikipedia. Squad data on Turkey was absent for two periods in the main source, and the desired information was obtained through the source *https://www.national-football-teams.com*. For every European team that entered either tournament ∈ {Euros, World Cup} over the period 1970 to 2018, we obtained information on players' names, their ages, and their minutes/appearances in the competition at each stage ∈ {Qualification, Finals}.[8]

3.2. Ethnicity of players

For societies with patrilineal surnames customs, surnames have been used as reliable indicators of population structure and relatedness by the genetic literature (Piazza et al., 1987; Jobling, 2001). The use of surnames is also not new to the economic literature. For instance, works by Kerr and Kerr (2018), Clark (2015) and Buonanno and Vanin (2017) in different fields of economics use surnames to predict ethnicity and community relatedness. We follow this global approach to characterize each national team's ancestral diversity. We obtain data on each surname's geographical distribution from the web source *forebears.io*, which presents a set of country-level statistics for various surnames.

More specifically, for each unique surname in the full list of players in our dataset, this source provides the three countries ($country_1$, $country_2$, $country_3$) displaying the highest incidences (i.e., the number of people having that surname in a particular country) and the highest frequencies (i.e., percentage of people having that surname in a particular country) of that specific surname. We then

[7] Another related paper using clubs and not national teams is Haas and Nüesch (2012). This study uses match-level panel data (ranging from 1999 to 2005) from the German Bundesliga, employing the nationality of team members. It documents a negative effect on the number of points received given the game outcome, the goal difference, and an average of individual players' performance evaluations made by experts. In addition, Vasilakis (2017) examines how the increase in mobility has reshaped the players' market among clubs and produced distributional effects in terms of performance and wages.

[8] Given the full name lists, we proceeded with a splitting to separate the father name information. We focus on father surnames for cross-country comparability.

Table 1
Predicted origins for Belgium, 1998 and 2018.

	BELGIUM TEAM, 2018 World Cup Finals
Adnan_Januzaj	Kosovo
Axel_Witsel	Netherlands
Dedryck_Boyata	DR Congo
Dries_Mertens	Belgium
Eden_Hazard	United States
Jan_Vertonghen	Belgium
Kevin_De_Bruyne	Belgium
Koen_Casteels	Belgium
Leander_Dendoncker	Belgium
Marouane_Fellaini	Morocco
Michy_Batshuayi	Belgium
Mousa_Dembélé	Mali
Nacer_Chadli	Morocco
Romelu_Lukaku	DR Congo
Simon_Mignolet	Belgium
Thibaut_Courtois	France
Thomas_Meunier	France
Thomas_Vermaelen	Belgium
Thorgan_Hazard	United States
Toby_Alderweireld	Belgium
Vincent_Kompany	DR Congo
Yannick_Carrasco	Spain
Youri_Tielemans	Belgium

	BELGIUM TEAM, 1998 World Cup Finals
Bertrand_Crasson	Belgium
Danny_Boffin	Belgium
Dany_Verlinden	Belgium
Enzo_Scifo	Italy
Eric_Deflandre	Belgium
Eric_Van_Meir	Belgium
Filip_De_Wilde	Belgium
Franky_Van_Der_Elst	Belgium
Gert_Verheyen	Belgium
Glen_De_Boeck	Belgium
Gordan_Vidovic	Bosnia and Herzegovina
Lorenzo_Staelens	Belgium
Luc_Nilis	Belgium
Luis_Oliveira	Brazil
Marc_Wilmots	Belgium
Mbo_Mpenza	DR Congo
Mike_Verstraeten	Belgium
Nico_Van_Kerckhoven	Belgium
Philippe_Clement	France
Philippe_Vande_Walle	Belgium
Vital_Borkelmans	Belgium
Émile_Mpenza	DR Congo

Notes: Example of predicted origins for the Belgian squads in the 1998 and 2018 World Cup final stage.

identify the best-predicted country $i*$ for a surname as the country i associated with the highest value of the variable ($Incidence_i * frequency_i$, $i \in country_1, country_2, country_3$). This procedure avoids favoring very small countries, which would occur if we looked only at the frequency (e.g., virtually every surname in Monaco has very high frequencies). Further, it avoids favoring massive countries, as would happen if one relied on the incidence only (e.g., countries like the U.S. have generally higher incidences, even for rare surnames).[9] Our website of choice has the important feature of delivering accent-sensitive information, which increases precision when mapping a surname and a country of origin.[10]

3.3. Examples of the algorithm prediction results

It can be expected that the matching algorithm is efficient but not perfect. To measure the size of errors, we performed a manual validation step. Here, we separated the probability of wrongly assigning the player a foreign origin and the probability of wrongly assigning the player a domestic origin. The manual checking revealed that measurement errors resulted almost exclusively from the first type. In our data, foreign predicted players accounted for about 37% of the sample. For these observations, online sources were used to check these predictions. To correct this, we applied a conservative approach, i.e. we only assigned a foreign origin if some online sources could confirm. This exercise shows that the match between the ethnicity and the surname is rather good and generates 85% of correct predictions[11] Two types of errors in terms of their incidence occur. We illustrate these errors using the case of the Belgian national team for two specific years, 1998 and 2018.

Table 1 provides the line-ups of the Belgian National team for 1998 and 2018 (World Cup final stages) along with the predicted origins. The most detrimental error is the case of the striker Batshuayi which is spuriously attributed to the Belgian ethnicity rather than to the Democratic Republic of the Congo. This error is because this surname is rare, and the coverage of surname incidence in the DRC is rather poor. Nevertheless, most prediction errors have little if no impact on the diversity level. The reason is that surnames have either some French or Dutch connotations. This type of error leads to spurious predictions in the case of Courtois, Lambert and Meunier on the French side and Van Der Linden or Thissen in the Dutch case. Nevertheless, when attributed to an ethnicity of a neighboring country, there is no impact on the diversity measure since the ancestral distance between Belgium and these countries is zero. The errors outlined in the Belgian case are also due to the particular linguistic situation of the country, with official languages (French, Dutch, and German) originating in the neighboring countries. These errors are lower in unilingual countries, representing the overwhelming proportion of countries in our sample.

[9] A first manual cleaning was performed using a language detection algorithm in Python. Specifically, we used language-predictive libraries (TextBlob, langdetect) in Python to check whether the surname prediction coming from our algorithm was in line with these library-based predictions. With this approach, in some minor cases, we corrected a minority of surnames manually.

[10] Building a small sample of 314 recent national teams' players, whose ethnicity was found through a set of online newspapers, the forebears.io based technique performed better than two alternative measures considered: www.name-prism.com/ and http://abel.lis.illinois.edu/cgi-bin/ethnea/search.py. The results are not reported here in the interest of space but can be obtained upon request.

[11] More details are provided in Section OB of the Online Appendix.

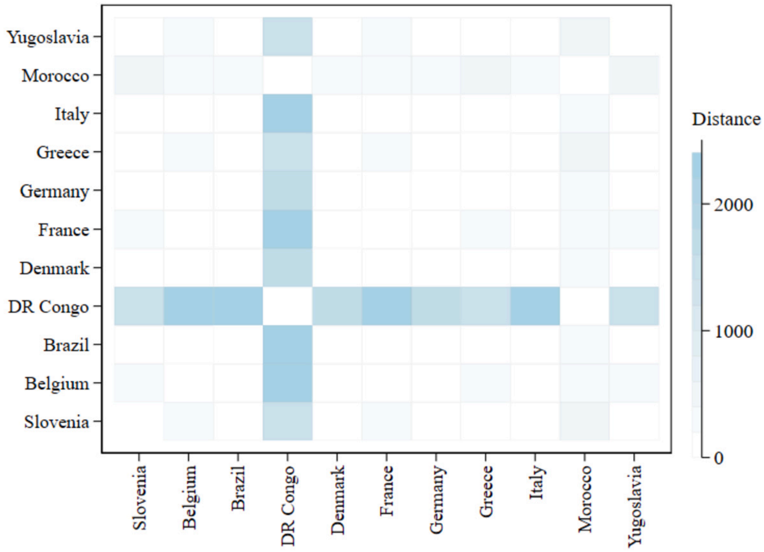

Fig. 1. Belgian squad's origin groups in 1996 and 1998 qualification stages.

Another interesting mistake is the case of Eden Hazard, who is predicted to have U.S. origins.[12] This seems at odds with information available from, e.g. genealogical providers (see https://en.geneastar.org/genealogy/hazardeden/eden-hazard). The player has Belgian ancestors until the sixth generation: Celestinus Desiderius Joseph Hazard (1783-1851), born in Brabant Wallon, Belgium. The surname comes from Medieval England. It is plausible that some Medieval ancestors not recorded in the genealogy moved from the U.K. to Belgium during the Middle Ages. However, we claim that our diversity measure is not driven by this type of error but rather by the diversity arriving from migrations a generation or so before. Take the following example. At the qualification stage of the Euros 1996, the Belgian squad had a diversity score of -.57, i.e. roughly half a standard deviation below average. At the qualifications of the following 1998 World Cup championship, the squad increased its diversity by roughly one standard deviation, reaching a value of .48 - i.e. roughly half a standard deviation above average. Descriptively, the set of origins predicted for the squad of 1996 where: Belgium, with a share of roughly 77%, Greece (due to Manu Karagiannis), Brazil (due to Luis Oliveira), Italy (due to Enzo Scifo and Alain Bettagno), Germany (due to Josip Weber, Philippe Albert and Georges Grün), France (due to Régis Génaux), Slovenia (due to Dirk Medved).

More broadly, the heatmap of Fig. 1 shows the variation in ancestral distances across these origin groups, as reported in the dataset by Spolaore and Wacziarg (2009). Notice, for example, that Brazil has a distance of 0 from Italy, as the dominant origin group set by Spolaore and Wacziarg for Brazil is Italian. Similarly, Slovenia and Greece have a zero distance, as they are both coded as predominantly Greek. Overall, European origins are close to each other regarding such a distance metric. In the 1998 World Cup Qualification squad, the share of predicted Belgians decreased marginally, and the set of foreign origins stayed relatively similar to the one above, but with the addition of two new and extra-continental origins: DR Congo, as represented by Emile and Mbo Mpenza, and Morocco, as represented by Nordin Jbari. As visualized in Fig. 1, these two origin groups, and DR Congo in particular, bear higher values of ancestral distances than the other - mainly European - origins. This illustrates that wrong assignments of players with Belgian origins have little impact on the bias in measuring the overall diversity at the team level.

Diversity increases through two effects: a decrease in the shares of the most represented origin groups and an increase in the number of distant origin groups. While some measurement errors exist due to manual cleaning, our method performs exceptionally well in capturing the second-generation migrants who may still contribute to the team's diversity (e.g., French national Zinedine Zidane was born in Marseille and is of Algerian descent).

3.4. Ancestral diversity

Diversity Div_{ist} of team i at time $t \in \{1970, ..., 2018\}$ and at competition stage s is given by:

$$Div_{ist} = \frac{1}{S_t} \sum_{j=1}^{N_{it}} \sum_{k=1}^{N_{it}} (p_{jt} p_{kt} d_{jk}), \ j \neq k \tag{1}$$

where p_{jt} and p_{kt} are the shares of players on the team (predicted to be from origin j and k respectively) belonging to the set of origins $\{1, ...N_{it}\}$ in team i for stage s of championship t. The fraction $\frac{1}{S_t}$ is a normalization factor for different squad sizes reported on the web source for the qualification stages. d_{jk} is the genetic distance between origin j and origin k, belonging to the set of

[12] We thank an anonymous referee for pointing this out.

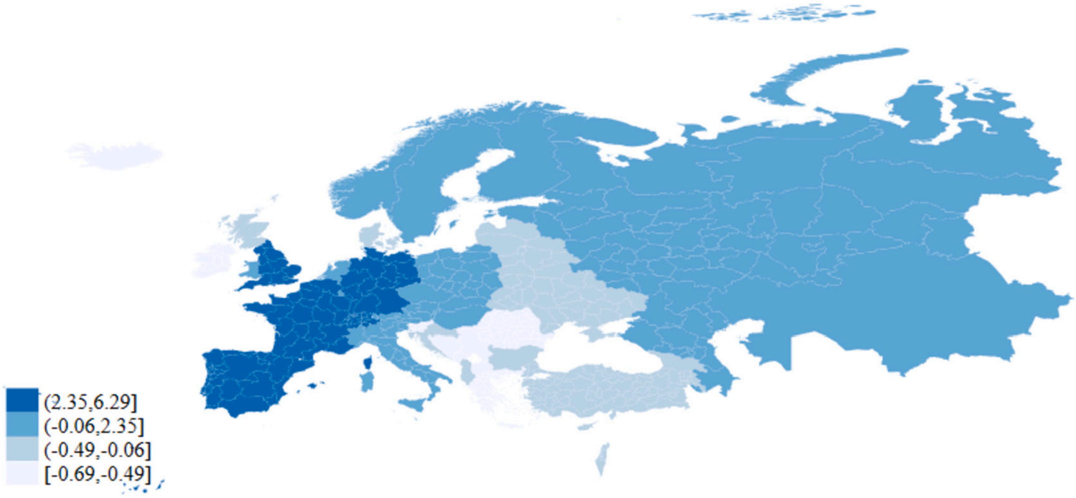

Fig. 2. Diversity of national teams, EURO 2016, finals.

surname-predicted origins in the squad. We use ancestral distances similarly to Alesina et al. (2016a), implying that our indicator can be seen as a weighted average of ancestral distances over all origin pairs in the team. Data on bilateral ancestral distance scores d_{jk} come from Spolaore and Wacziarg (2009) who adapt distance matrices from the genetic literature (Cavalli-Sforza et al., 1994). Spolaore and Wacziarg (2009) quantify a genetic distance - a molecular clock - that measures the time since two populations shared a common ancestor. Similarly to Dickens (2018), we interpret this index of population relatedness as ancestral diversity. Players originating from populations with a narrow ancestral distance have a high likelihood of similar traits and ideas, and thus they may possess fewer novel ideas and attributes to share. However, players from populations with significant ancestral distances have a higher chance of holding a broader spectrum of non-overlapping and more complementary traits. This approach is comparable to Ingersoll et al. (2017)'s linguistic diversity and does not profoundly differ from linguistic diversity indicators proposed in the seminal work of Greenberg (1956) and re-elaborated in Fearon (2003). The explicit consideration of ancestral distances, key to our framework, allows more weight to be given to more ancestral distant origins.[13]

As a snapshot example, we report in Fig. 2 the cross-country diversity variation in the EUROs 2016. A general pattern appears with Eastern Europe teams presenting lower diversity levels, whereas Western Europe teams show higher levels of diversity, likely reflecting accumulated migration inflows over the recent decades.

3.5. Measuring performances of national teams

Our main variable of national teams' performance is measured at the match level and has a dyadic nature. The performance of one team also depends on the performance of the opponent. More specifically, our benchmark performance outcome is the goal difference, but we also consider other bilateral performance measures for robustness checks. Data at the match level come from the collection *International Football Results from 1872 to 2020* assembled by Mart Jürisoo (2020). It includes a complete and updated men's football international matches dataset.[14]

Fig. 3 provides a summary of the critical components of the bilateral measure, i.e., scored and received goals, broken down between home (left panel) and away (right panel) matches. The figures confirm that, on average, teams perform better at home than abroad, a prominent feature in football competitions. We will account for this feature in the econometric specification involving the bilateral dimension of performances.

Table 2 provides summary statistics for the main variables. The complete list of countries included in the sample is given in the Online Appendix.

3.6. Other variables

We include various covariates affecting the performances of national teams. These variables are observed at either the team or the country levels. In our benchmark estimates, at the team level, we include the average age in its quadratic form and the players' appearance time variation for the team. We also include the standard deviation in the team members' minutes to disentangle better possible turnover decisions or other strategic concerns that may reflect the team's talent distribution. Country-level controls involve population (in millions), (the log of) GDP per capita, and past immigration stocks. Population data are retrieved from the

[13] Andorra and Liechtenstein are not in our sample as they are not part of the Spolaore and Wacziarg's dataset.

[14] Retrieved on January 2020 https://www.kaggle.com/martj42/international-football-results-from-1872-to-2017/tasks (version 4)

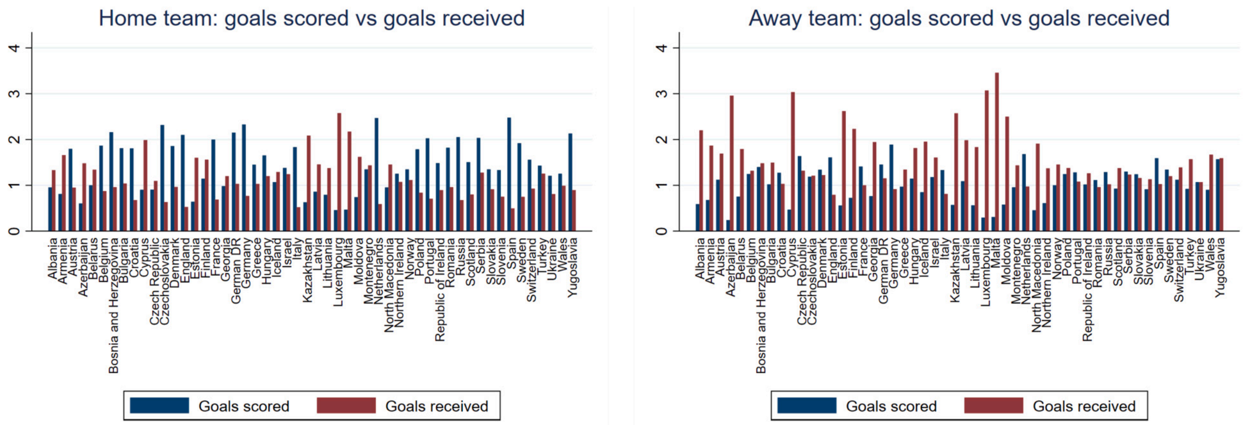

Fig. 3. All-time goals scored and received, all national teams.

Table 2
Summary statistics table.

	Mean	Standard deviation	N	Min	Max
Performance measures					
Goal difference	0.482	2.068	3877	-8.000	11.000
Goal difference, hyperbolic sine	0.276	1.223	3877	-2.776	3.093
Diversity measures					
Bilateral diversity	0.002	1.044	3877	-5.189	5.372
Bilateral diversity, appearance	0.001	1.042	3877	-6.507	5.182
Bilateral diversity, SW	0.002	1.039	3877	-4.714	5.356
Diversity, home	0.052	1.048	3877	-0.707	6.626
Diversity, away	0.050	1.041	3877	-0.710	6.775
Team level variables					
Stand. dev. squad age, home	3.686	0.884	3877	1.953	13.278
Squad age, home	27.659	1.030	3877	24.286	31.045
Stand. dev. squad age, away	3.683	0.884	3877	1.953	13.278
Squad age, away	27.670	1.028	3877	24.286	31.045
Squad age, squared, home	766.094	56.999	3877	589.796	963.820
Squad age, squared, away	766.702	56.886	3877	589.796	963.820
Stand. dev. appearances, home	236.287	63.793	3877	59.594	451.440
Stand. dev. appearances, away	235.348	64.335	3877	67.750	451.440
Foreign coach, home	0.176	0.381	3877	0.000	1.000
Foreign coach, away	0.178	0.383	3877	0.000	1.000
Coach age, home	51.126	8.118	3877	28.000	74.000
Coach age, away	51.194	8.117	3877	28.000	74.000
Macroeconomic variables					
Population (mln), home	24.493	29.011	3877	0.224	148.689
Population (mln), away	24.263	29.025	3877	0.224	148.689
Log of GDP/capita, home	9.692	1.028	3877	6.836	11.584
Log of GDP/capita, away	9.682	1.033	3877	6.836	11.584
Log immig. stocks, 18y lag, home	12.665	2.461	3576	0.000	16.294
Log immig. stocks, 18y lag, away	12.630	2.459	3576	0.000	16.294
Adversary's strength, home	1674.520	108.400	3877	1416.287	2117.771
Adversary's strength, away	1673.245	111.092	3877	1400.824	2140.289
Contiguity	0.095	0.293	3877	0.000	1.000
Same nation	0.021	0.144	3877	0.000	1.000
Common language	0.050	0.219	3877	0.000	1.000
IV					
IV, home vs. away	0.000	1.000	3877	-3.631	3.646

Notes: All specifications involve a dataset of matches held in the qualification and final stages of the EURO or World Cup, where both adversaries belong to the UEFA affiliation.

Centre d'Études Prospectives et d'Informations Internationales (CEPII) from 2014 and then completed using World Bank data for the most recent values. GDP data (at constant 2015 prices) are extracted from the United Nations data office[15]; immigrant stocks were retrieved from the World Bank and started in 1960. When lagged, estimates that include this covariate will reduce the sample size to more recent years (beginning in 1978). We provide extensive information on all variables in our regressions in the Appendix.

[15] National Accounts Section of the United Nations Statistics Division: National Accounts Main Aggregates Database. https://unstats.un.org/unsd/snaama/Basic.

3.7. The instrument

We aim to estimate a causal relationship between the football teams' ancestral diversity and their performance. As we include a set of controls at team and national levels, together with team-level fixed effects and country pair fixed effects, concerns regarding the endogeneity of our variable of interest are mitigated. Still, a set of current political, cultural, economic or institutional conditions that are not considered in our framework may fall into the error term, resulting in a potential omitted variable bias. For example, naturalized players and, more generally, players with more than one nationality may be able to choose which national team to play for. They may have incentives to play for countries offering specific conditions. These conditions may reflect financial, cultural, institutional and football-related resources that may correlate with the team's performance. The squad selection process may also reflect the cultural or institutional characteristics of the countries. If this selection is carried out to favor native players over second-generation migrants, this could cause inefficiencies in the talent selection, thus undermining the teams' performance.

Theoretically, the sign and the direction bias in the estimation due to the omitted variables or the self-selection of players with multiple nationalities are challenging to anticipate and are primarily empirical issues. Foreign-origin players with multiple passports might choose countries with a reasonable probability of success to benefit from financial rewards and increase their attractiveness. In this case, naive estimates would result in an overestimation of the impact of ancestral diversity on performance. Nevertheless, there are many cases in which these players favor joining a weaker team as it increases their chance of being selected.[16] If this self-selection pattern dominates, a naive estimation will rather underestimate the role of ancestral diversity.[17]

While part of these issues may be fixed over time, we allow for time variation in these characteristics and carry out an instrumental variable approach to ensure causality under these circumstances.[18] We use the level of ancestral diversity of past immigration of the country as an instrument. In the structural equation, we account for the size of past immigration and the contemporaneous level of GDP per capita. Introducing these controls mitigates the concerns of a direct impact of our instrument on the performance of the national soccer team through the potential beneficial economic effects of past immigration.

In order to play for national teams, players need to comply with strict conditions of eligibility and, in particular, be nationals of the represented country.[19] Eligible players would therefore be either naturalized immigrants or children of natives or second-/third-generation immigrants in their adopted country.[20] National teams' diversity is therefore driven by the immigration history of the previous generation of their representing country (as well as the degree to which access to nationality for second-generation migrants is possible). Countries with low immigration rates will therefore exhibit, everything else being equal, a low diversity transmitted over time within the same native population. This would also be true in countries with high immigration rates but with a concentrated origin of immigrants. High diversity will be in countries with significant immigrant flows originating from diverse areas. As past immigration to a destination country translates into heterogeneity in its nationals, we build a historical measure of country diversity that should predict how diverse the national team will be years later.[21]

To construct our instrument, we use data on the ethnic composition of countries provided by the University of Illinois Cline Center for Advanced Social Research. The Composition of Religious and Ethnic Groups (CREG)[22] is a time-varying measure that involves country-specific information on 165 large countries. In the sample, ethnic groups are given narrow definitions (e.g. *Russian*, *Romanian*, *Scottish*), which we converted to a reference country. The data provider uses the classification "others "to group information on one or more unknown ethnic minorities.

We build a measure of lagged country diversity, following the same diversity formula described above. We produce the following country-level index IV_{it} that we use for the country's team:

$$IV_{it} = \sum_{j=1}^{N_{i,t-18}} \sum_{k=1}^{N_{i,t-18}} (p_{jt-18} p_{kt-18} d_{jk}),\ j \neq k \tag{2}$$

where p_{jt-18} and p_{kt-18} are shares of origins j and k immigration stocks, belonging to the set origins in country i at time $t-18$. The instrument is used for the qualification of the final phase. As a decision rule, the group "others" in country i was assigned a median distant country j from the Spolaore and Wacziarg (2009) dominant groups distance measure. The resulting variable was lagged to account for second-generation migration effects. While the lag choice is somewhat arbitrary, a higher lag would increase the data loss. For this reason, we use in our benchmark analysis an 18-year lag to limit the reduction in the final sample size, but 20-year and 22-year lags are also considered for sensitivity checking. An inconvenience of the CREG dataset is that there are no data for a set of small countries (Kosovo, Malta, San Marino, Luxembourg, Montenegro, Faroe Islands), plus France and Iceland. We complement the data with Özden et al. (2011) Bilateral Migration Database to account for this issue. For the years 1960-2020, this data source

[16] A good example is the one of Mehdi Carcela-Gonzalez, who could choose between Spain, Belgium and Morocco. Born, playing and living in Belgium, he chose Morocco, which, at that time, was ranked much lower than Belgium and Spain.

[17] Another example of underestimation due to confounding factors would be the case of a country in which a relatively high level of diversity would create internal organizational problems, generating conditions detrimental to the national team performances.

[18] Note that the IV procedure might also solve part of the measurement errors due to the matching algorithm explained before.

[19] FIFA added eligibility restrictions for players representing national teams in 1962: 1. Players must be naturalized citizens of the country they represent. 2. If a player is in a national team, he is ineligible to represent another nation. 3. Exceptions only matter if geopolitical changes in the countries occur. See Hall (2012).

[20] This would have some variation on the citizenship granting process that follows from the destination countries' law.

[21] On a similar vein, an instrument that matches population-level to firm-level diversity is employed in Anderson et al. (2011).

[22] Cline Center for Advanced Social Research (2020).

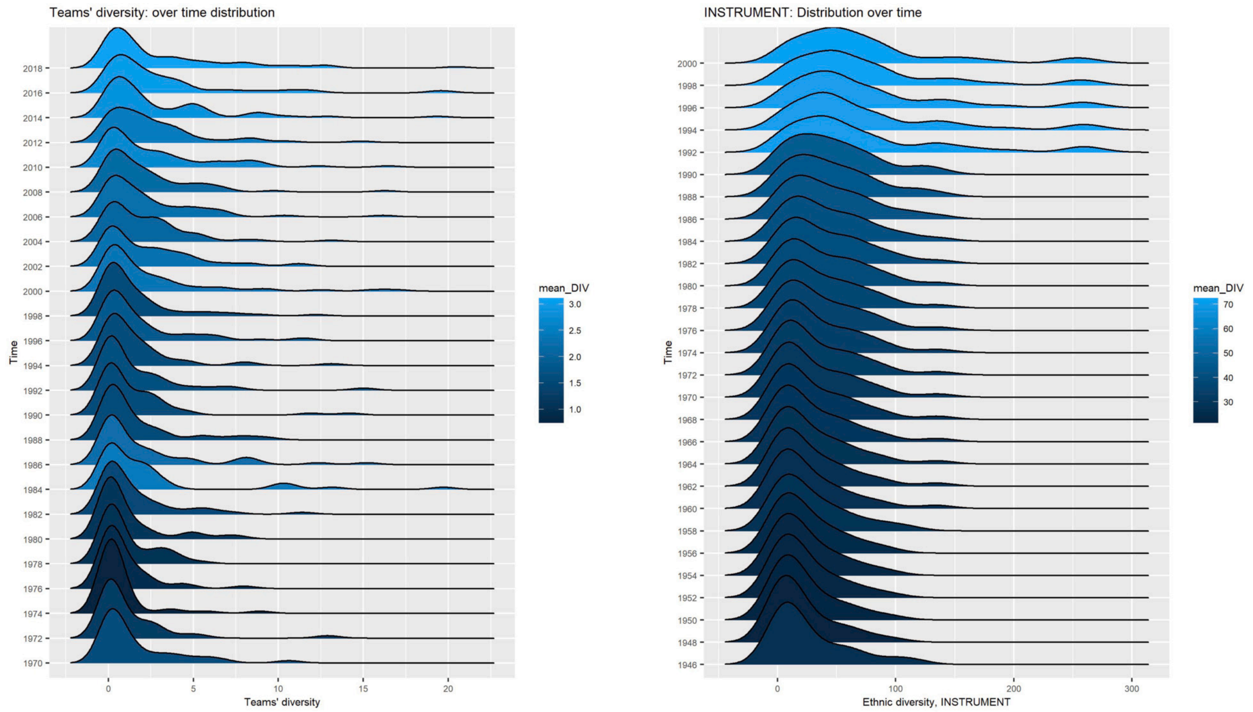

Fig. 4. IV diversity over time.

aggregates records from different sources via a state-space model, providing a global bilateral database on the stock of migrants according to their country of birth at the year level.

The resulting distributions are presented in the right panel of Fig. 4 and are compared with the team diversity measure (left panel). This picture points to an increase in national teams' diversity that is matched visually by a positive evolution in our baseline instrument's lagged mean national diversity. This pattern is broadly in line with van Campenhout et al. (2019), which also suggests a growing trend in diversity occurring over time for the World Cup teams due to the countries' migratory histories and citizenship regimes. However, the growth in diversity has been uneven across countries, as shown by the longer right tails. Although we formally assess the strength of our instrument in the following sections, the patterns in the plots of Fig. 4 seem broadly similar in the national teams' diversity and the diversity of the whole population.

Our instrumentation strategy also relies on the idea that players in the national representative team with foreign origins come from the second-generation immigrant population. Nevertheless, access to nationality for second-generation immigrants is a necessary condition for the existence of such a mechanism since citizenship is a condition of eligibility for the players. In other terms, if this mechanism of the instrumentation strategy is prevailing, variations across hosting countries in the access to citizenship for immigrants should affect the strength of past immigration as an instrument of genetic diversity. To document the role of access to nationality, we look at two specific cases involving countries that implemented reforms facilitating the acquisition of nationality for immigrants. The first case is the one of Germany, which implemented two reforms in the 90s that favored the acquisition of German nationality for second-generation immigrants. The Alien Act of 1991 (Auslanddergesetz) introduced explicit criteria for naturalization regarding age-dependent residency requirements. The Citizenship Act of 2000 introduced birthright citizenship, both for immigrants and second generation migrants born in Germany. Both reforms increased the number of naturalized foreigners, with potential consequences in terms of integration and assimilation.[23] The second case concerns Switzerland, which was subject to two reforms favoring the acquisition of Swiss nationality (Hainmueller and Hangartner, 2019). The 1992 reform allowed immigrants to hold multiple citizenships. In 2003, a series of rulings by the Swiss Federal Court forced most municipalities to change their decision-making process from direct to representative democracy, which resulted in a surge of naturalization rates by about 60% (Hainmueller and Hangartner, 2019).

Fig. 5a and 5b provide for each country the evolution over time of naturalization and the level of ancestral diversity of the national soccer team. Both figures confirm the increase in naturalization observed in the aftermath of the reforms. More importantly, in both cases, this increase resulted in a higher level of ancestral diversity in the national team. This provides evidence in favor of the vital role of the legal conditions of access to nationality for immigrants set and their children by a country for the future performances of the national team. From a statistical point of view, this analysis involving the role of access to citizenship also further relevance of our IV strategy.

[23] See Gathmann and Garbers (2023) and Gathmann and Keller (2018), among others.

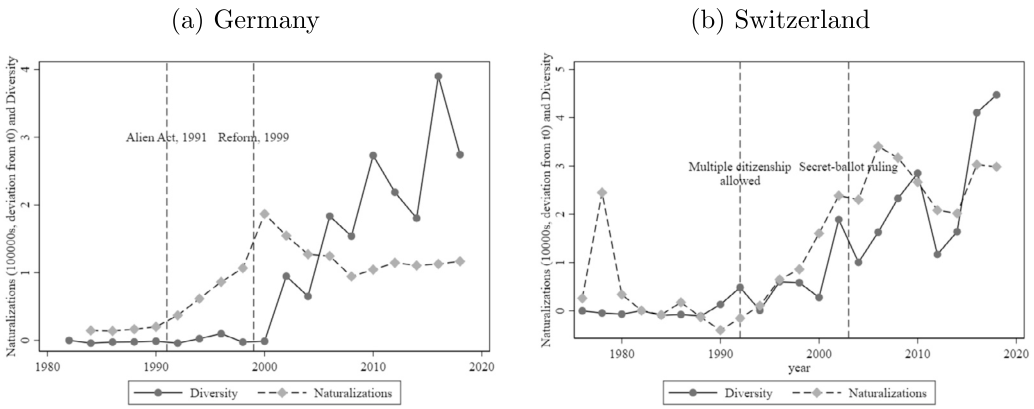

Fig. 5. Reforms of access to nationality and ancestral diversity.

4. Empirical analysis and results

We first carry out OLS estimations to obtain the relationship between diversity and football performances. Since the estimations in these naive OLS regressions are likely to be biased by some confounding factors as well as self-selection patters of players with multiple citizenship, we then move to the instrumental variable estimations to uncover a causal link between diversity and performance.

4.1. Benchmark estimations

Our benchmark estimation is as follows:

$$Performance_{ijst} = \alpha_i + \alpha_j + \alpha_s + \alpha_t + \beta(Diversity_{ist} - Diversity_{jst}) + X'_{ist}\Gamma + X'_{jst}\Sigma + X'_{ijst}\Delta + \epsilon_{ijst} \tag{3}$$

where the baseline performance indicator $Performance_{ijst}$ is the goal difference between home team i and away team j facing one another at stage s of championship t. The match takes place in either or both stages s = {qualification, finals} of the two types of international tournaments, i.e., the FIFA World Cup and the UEFA Euro Cup in $t \in$ {1970, 1972, 1974,....2016, 2018}.[24] Our regressor of interest is the difference in levels of ancestral diversity $(Diversity_{ist} - Diversity_{jst})$, where diversity of each team is computed as detailed in Equation (1). We include (hosting and receiving) team, stage and time fixed effects $\alpha_i, \alpha_j, \alpha_s, \alpha_t$ in all our specifications. Vectors X'_{ist} and X'_{jst} include the set of team controls explained in the previous section, whereas X_{ijst} includes pair controls. While fixed effects capture the effect of unobserved factors that are either constant over time or across countries, the set of covariates X'_{ist} and X'_{jst} and X_{ijst} arguably accounts for other time-varying observed factors. For instance, a country's financial resources may positively correlate with its national team's performance. At the same time, these resources may have acted as a pull effect for immigration, which would result in a higher level of diversity. We therefore include the log of GDP per capita and lagged immigration in our controls.[25] The demographic size of a country is in our controls as well, as it could also be linked to its diversity and the probability of having talented eligible players in every cohort.

Football matches can also be impacted also by (current or historical) dyadic features between the two countries. For instance, rivalry is boosted when countries are neighbors or share a common colonial history. To account for that, we also control for the so-called geo-political factors. These include (current or historical) contiguity, sharing a common language, and belonging to the same country at some stage in time.[26] As an alternative, we also include in some regressions pair fixed effects that capture the role of these geo-political covariates as well as of all unobserved time-invariant dyadic factors.[27]

4.2. Results

Our baseline findings are shown in Table 3. They include robust standard errors clustered at the pair level. Team i is referred to as the home team, and team j is the away team. The key dependent variable for this framework is the goal difference as we perform the analysis at the match level. Results are provided from the simplest specification (no controls) to the most complete one (all types

[24] The year itself of the event reveals which tournament is played, so there is no need for a tournament fixed effect.

[25] This covariate allows one to isolate the role of diversity in past immigration flows in the instrumental variable from its direct impact on performance by, for instance, increasing the talent pool.

[26] Note that due to a historical agreement in the early phase of international football, the four main regions of the U.K. (England, Scotland, Northern Ireland, and Wales) compete as separate teams.

[27] Note that the inclusion of the pair FE is highly depending on the data as the effect is only identified from matches between teams playing several times against one another over the period.

Table 3
Performance and ancestral diversity.

	Dependent variable: goal difference							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Variable of interest								
Bilateral diversity	0.075*	0.018	0.016	0.020	0.777**	1.543**	1.345**	1.786**
	(0.042)	(0.040)	(0.040)	(0.053)	(0.299)	(0.535)	(0.422)	(0.822)
Control variables								
Log of GDP/capita, home		-0.012	0.019	-0.039		0.107	0.079	-0.058
		(0.207)	(0.208)	(0.303)		(0.259)	(0.246)	(0.384)
Log of GDP/capita, away		-0.467**	-0.463**	-0.099		-0.727**	-0.630**	-0.200
		(0.216)	(0.217)	(0.301)		(0.291)	(0.267)	(0.430)
Log immig. stocks, 18y lag, home		0.067	0.050	0.032		0.156**	0.151**	0.196*
		(0.043)	(0.045)	(0.067)		(0.062)	(0.063)	(0.115)
Log immig. stocks, 18y lag, away		-0.096**	-0.100**	-0.064		-0.156**	-0.180**	-0.163*
		(0.045)	(0.047)	(0.065)		(0.060)	(0.060)	(0.094)
Population (mln), home			-0.004	-0.003			0.002	0.006
			(0.003)	(0.004)			(0.004)	(0.007)
Population (mln), away			-0.001	-0.003			-0.008*	-0.013*
			(0.003)	(0.004)			(0.004)	(0.007)
Observations	3877	3568	3568	2832	3877	3568	3568	2832
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					51.57	22.32	33.24	9.76
Team FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes		Yes	Yes	Yes
Geo-political controls			Yes				Yes	
Pair FE				Yes				Yes

Notes: Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970-2018 (for columns 1 and 5) / years 1978-2018 (for all other columns). Dependent variable: Goal difference. OLS results appear on the left (columns 1 to 4). Column 5 to Column 8 display IV results. The first 3 columns of OLS and IV include individual team and year fixed effects, as well as a stage dummy Columns 4 and 8 replace individual-team with pair fixed effects. Standard errors are clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F-test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

of control and pair fixed effects). Table 3 presents results in the left panel (columns 1 to 4), where potential endogeneity concerns arise, and the IV results on the right (columns 5 to 8). Using OLS, diversity is positive but only significant in column 1, at the 10% level, while it becomes significantly positive at the 5% level in all IV specifications. Past immigration stocks and population, when significant, increase the relative team performance, suggesting an effect related to the enlargement of the talent pool. The exact relation appears for GDP per capita, which is a positive determinant of performance, reflecting that teams from more prosperous countries can benefit from better resources, improving performance.[28]

Concerning the economic magnitude of our coefficient of interest, in the IV specifications, a one-standard-deviation increase in the diversity measure leads to a non-negligible increase in the goal difference of 0.77 to 1.79 units. Our preferred specification (column 7) yields an effect in terms of goal difference of about 1.35 goals. The results suggest that estimations obtained with a naive approach (OLS) or a misspecified model (column 5) are subject to a negative bias. This might suggest a self-selection pattern of players with multiple citizenships favoring weaker national teams to increase the probability of being selected. It might also be due to a correlation between ancestral diversity and unobserved factors that tend to negatively affect the performances of the team.[29]

28 Following Ashraf and Galor (2013), we also tested a quadratic version of equation (3) in which squared diversity enters as an additional explanatory variable. We do not get significance of this additional term (either for OLS or IV estimates). We therefore fail to document a possible negative impact of diversity beyond a certain level (due to disagreements or miscoordination for instance). One possible explanation for this is the coordination role of the coach. Another statistical explanation is that in almost none case, the level of diversity is high enough to reach the turning point of the role of diversity. Indeed, even in highly diversified teams such as France, players coming from the native population are dominating the line-up of the national squad.

29 For instance, in column 5, neglecting current immigration yields a lower impact of diversity. It could be that countries with current high immigration levels tend to have higher levels of ancestral diversity and, at the same time, tends to face a negative atmosphere around the national team, affecting its performance negatively. A well-known example of such a case was that, when playing against Algeria in 2001 and Morocco in 2007, the French national team was booed during the national anthems and the match. The match against Algeria was even stopped before the end.

5. Robustness and placebo analysis

5.1. Robustness checks

In the following sections, we conduct several sensitivity exercises to assess the impact of our methodological options in the benchmark estimations.

Other performance indicators in a match. We first check the robustness of our results by using the probability of winning and the number of goals scored or taken as alternative measures of the teams' performances. Considering the first alternative, Table 4 proposes a linear probability model with the probability of winning. The outcome in this set of regressions takes the value of 1 for a victory of the home team, 0.5 for a tie and 0 for a loss. We find that a standard deviation increase in relative diversity is crucial for the team victory, which increases by 20 to 34% percentage points in our IV results.

A unilateral setting. We check the robustness of our findings by considering an absolute measure of the performance of team i based on its rating. This setting refers to the unilateral dimension of the performance data. In this unilateral setting, our performance indicator is the Elo score of a team. Updated after each game, the Elo score of a team is a function of its previous score, the realized and the expected results (given the opponents' relative strength) and the tournament's importance. Summary statistics and a complete description and formula are found in the Online Appendix. Based on match-level information, we construct Elo ratings relative to the EURO and World Cup qualifications results and final stages for our whole sample. Our measure is the change in the score from the beginning to the end of the championship stage. For team i, performing in stage s, at Championship t, our baseline performance measure for the unilateral setting is therefore

$$Performance_{ist} = Elo\ score_{End,ist} - Elo\ score_{Beginning,ist} \tag{4}$$

We run our benchmark estimations using this performance indicator. As shown in Table 5, and similarly to the benchmark analysis, diversity positively affects the ranking of national teams. Our estimate of the effect of diversity is positive in all our specifications.[30]

Additional controls: initial strength of the team. To better assess the match-level dimension of our results, we propose a specification in which we control for the level of talent, which we proxy with the Elo score levels of each team at the beginning of the competition. Table 6 presents results that complement the previous outcomes with this additional control. As one could expect, the initial scores of the teams are significant, positive predictors of their relative performance. Nevertheless, the effect of diversity remains significantly positive in all the IV-based results, as in the benchmark. This suggests that diversity has a distinctive role in performance during the match and that positive skill complementarities manifested in the team's coordination.

Alternative regression methods. We first adopt a set of covariates comparable to our preferred baseline specification, column 7, but includes the richest set of controls and individual team fixed effects.[31] Columns (1) to (4) of Table 7 report the results of, respectively, a specification where diversity is replaced with its appearance's re-weighted measure[32]; a regression where diversity is computed with the alternative ancestral distance measure as proposed in Spolaore and Wacziarg (2009); a specification with a higher lag for our instrument (22 years) and a regression that adds information related to the team coaches as additional controls. Precisely, we control for age, tenure, a foreign nationality dummy, and a measure of coach quality for both the home and the away team. In this regression, the away team's foreign coach dummy is positively associated with the away team's performance, as is the coach quality measure (based on awards). The resulting coefficients are very comparable to the baseline evidence. A second check concerns the use of linear regression models. Since the goal difference is a discrete variable (between −13 and 12), the linear models may become less appropriate as they assume a continuous variable. We address this concern in two different ways. First, we perform an inverse hyperbolic sine (IHS) transform on the variable. This type of procedure has been proposed in the literature by Burbidge et al. (1988) as an alternative to the log transformation. Indeed, such a transformation allows for including variables that take zeroes and negative values while maintaining approximatively the same coefficient interpretation as the log form. Second, we conduct a Poisson-based regression with scores as our outcome of interest and present the results in a separate table. Column (5) results present the first alternative and suggest that a hyperbolic sine transformation does not lead to different outcomes in the results of interest: a positive coefficient for the diversity measure of roughly 0.83 is significant at the 1% level. Column (6) of Table 7 estimates a linear model on the number of goals at home as the dependent variable. The coefficient on diversity is significant at the 5% level and approximately 0.73. Finally, an alternative specification of bilateral diversity is proposed. Instead of the benchmark bilateral diversity measure corresponding to the difference ($Diversity_{home} - Diversity_{away}$), we allow the two terms to enter separately, allowing for the presence of a different effect for the home team and away team. Each term is instrumented, resulting in two first stages. Results indicate coefficients with opposite signs: the goal difference is, as expected, impacted positively by the home team and negatively by the adversary, with significance at a 5% level. Finally, in Table A10, we run Poisson regressions using as a dependent variable the number of goals made by the home team in one set of regressions and by the away team in a second set of regressions. Our findings remain robust to this check.

[30] For the interested readers, we run our entire analysis using this unilateral setting. This analysis is provided in the Online Appendix for readability.

[31] Pair-level fixed effects are very demanding as they imply that the only variation left is within a pair of adversaries that repeatedly play against each other. Therefore, we deem the specifications accounting for individual-level fixed effects as our preferred ones.

[32] Ingersoll et al. (2017) focus on football clubs and identify that cultural diversity on the pitch matters positively for performance. However, they find an insignificant effect for off-the-pitch interactions. To accommodate this possible heterogeneity, we also include minutes played as weights in our diversity calculations.

5.2. Placebo analysis

As a final analysis assessing the validity of our results, we perform a placebo analysis using national performances from athletics as the outcome variable. Since the main channel explaining the positive impact of ancestral diversity goes through the complementarity of skills at the team level, we should expect that ancestral diversity does not play any role in explaining the performances at the individual level. Athletics is an accessible and mostly individual sport. We, therefore, assume the national pool of talent that athletics federations can rely on is comparable to that of football. Suppose the placebo analysis returned significant coefficients of the football team's diversity index on athletics performance. In that case, we might be concerned that some omitted variable—such as a particular set of origins—would positively affect the national talent pool and our performance outcome. This mechanism may go beyond the size of lagged immigration, which we control for.

For the sake of this analysis, we extract information from Wikipedia about the total number of medals and gold medals won by each nation in the European Athletics Indoor Championships[33] and the European Athletics Outdoor Championships,[34] The European Athletics Outdoor Championships is an athletics event that started in 1934 with a quadrennial frequency until 2010 when it switched to a biennial frequency.[35] The number of athletes each national federation can enroll in any of these championships is based on their performance and is capped from above for each nation and discipline.[36] As noted above, we collect information on the number of medals each nation won in each championship. To match these data with our original biennial data of football events, we consider athletics championships held in year t (if t is an odd year) as having been held in $t + 1$. Whenever we have more than one event in the same year, we average the total national medals won by year. We, therefore, obtain two indicators of athletic performance at the national level: the number of total medals obtained by the national representatives and the number of gold medals. The results of the placebo exercise are reported in Table 8. Specifically, Table 8's dependent variables are from left to right the benchmark Elo score changes, the total number of medals and the total of gold medals.[37] The set of covariates is comparable to the rightmost column of our baseline tables. The coefficients of our diversity score in the placebo results are insignificant, suggesting that diversity in football teams does not impact the performances of an individual sport such as athletics. All in all, this strengthens the case of a positive impact of ancestral diversity through its impact on collective performance through the generated complementarity of skills.[38]

6. Discussion and mechanism

While our empirical analysis delivers some robust evidence of the influence of ancestral diversity on soccer performances, it is essential to reflect on the possible channels through which such an effect operates. We, therefore, aim to provide some indirect evidence in favor of potential mechanisms.[39] We evaluate hereafter the case in favor of two potential complementary channels through which ancestral diversity might impact performances.

The first channel we investigate operates through the complementarity in physical traits and technical skills associated with higher ancestral diversity. A homogeneous population will result in a team with relatively homogeneous physical traits and skills such as height, speed, movement coordination, dribbling, and tactical skills. Soccer performances tend to require some specificity in the physical traits and technical skills, depending on each player's role and position on the pitch. For instance, central defenders need to be tall and physically strong, while an essential skill for offensive lateral players is speed. A more diverse population will more likely provide a good pool of potential players for each position, resulting in better complementarity at the team level. We can call that the channel of complementarity. To investigate whether there is some support for this channel, we built a new dataset using information from the Electronic Arts FIFA football video game. We collect players' characteristics from the online platform https://sofifa.com/.[40] The website displays detailed data on the universe of players present in the editions of the video game FIFA (as long as they were present in the game modality "Career Mode") from 2007 to 2022. The game produces rich data on the attributes and skills of the players that closely follow the real athletes' characteristics and their changes over time. Within this list of attributes, we find body mass features (height, weight, and we computed the ratio), performance-based skills along the dimensions of attack (crossing, heading, ...), skill in dribbling (long passes, accuracy, control) and movement (e.g. acceleration, sprint, ...). We extracted national teams by year from the website database and matched it with our teams' data by national team and year, focusing on the final stages only to ensure a better squad size match.[41] Details on the players' attributes meaning can be found in Table A9. We then analyze the

[33] Wikipedia, "European Athletics Indoor Championships." Last accessed: June 2023, https://en.wikipedia.org/wiki/European Athletics Indoor Championships.

[34] Wikipedia, "European Athletics Championships." Last accessed: June 2023, https://en.wikipedia.org/wiki/European Athletics Championships.

[35] It is organized by the European Athletics Association (EAA), which is the continental committee of the worldwide International Association of Athletic Federations (IAAF). EAA is based in Switzerland (as are the UEFA and FIFA) and comprises 51 national associations (or members). EAA also organizes the European Athletics Indoor Championships, now a biennial event, but its frequency was yearly until 1990. A gap of three years passed between the 2002 and 2005's tournaments.

[36] European Athletics, "Competition regulations," Last accessed: June 2023, https://european-athletics.com/competition-regulations/.

[37] Notice that for this Placebo exercise, we use the unilateral dimension of football team performance introduced in the Robustness Analysis above as this unilateral measure is more appropriate for the athletics setting.

[38] We do not fully exclude the possibility that our results are particularly relevant for a specific set of countries where the link between the endogenous variable and the instrument is strongest. Given the different sizes of the OLS and IV coefficients, this may indicate the presence of LATE effects when the instrumental variable is employed. Given statistical power limitations, we do not further disaggregate this channel, limiting our results' rationalization to the general dimension.

[39] A definitive test of the existence of these mechanisms would require a fully structural approach and is obviously beyond the scope of this paper. Such an investigation is therefore left for future work.

[40] We thank an anonymous referee for suggesting this source.

[41] We use the 2007 edition to match 2006's World Cup data.

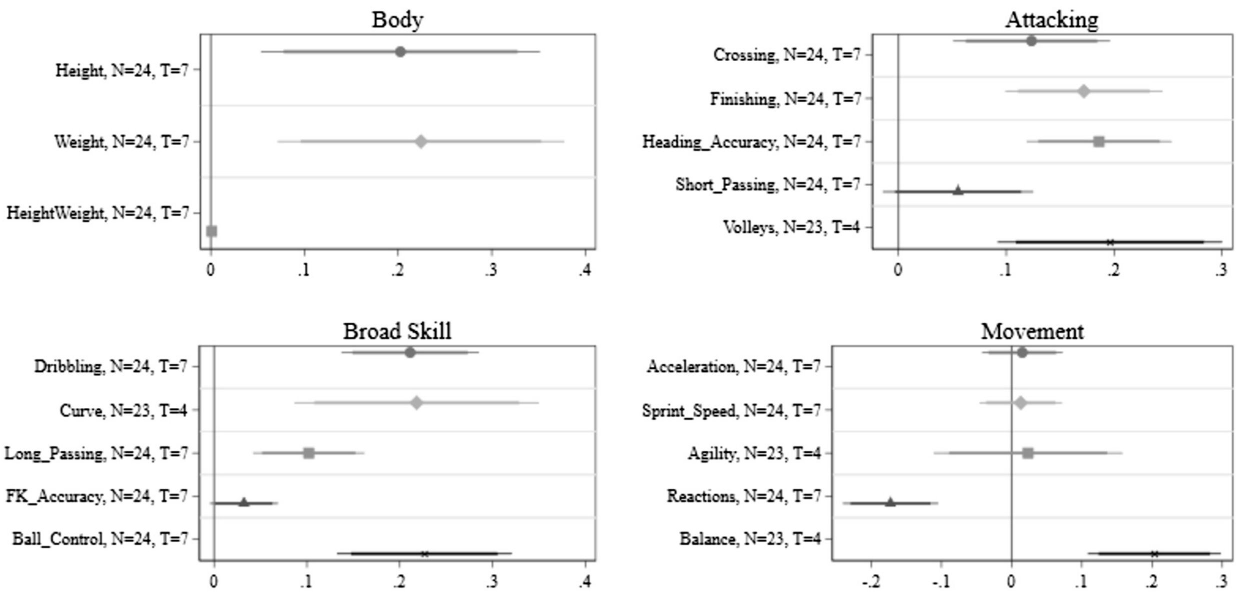

Fig. 6. Ancestral diversity and team features.

correlation between teams' diversity and the variation (standard deviation) in the players' attributes: body mass, attacking statistics, broad skills and movement. These relationships are shown in Fig. 6. Diversity (represented in the x-axis) positively and significantly correlates with the standard deviation of the team's features in most dimensions. Accordingly, these results support the idea that ancestral diversity improves complementary among different players in the team, ultimately improving teams' performances.

7. Conclusion

Diversity is a double-edged sword. Greater diversity benefits teamwork since teams can draw on a broader variety of skills and knowledge from diverse people. However, diversity might also lead to decreased team performance and effectiveness if more diversity brings a lack of coordination and increased conflict. This paper assesses the effect of ancestral diversity due to past migration flows on sports performance. To do so, we have built a new dataset that gathers information about the diversity of European national football teams playing in the World Cup or European Cup, qualifications and finals, and several time-varying performance indicators for each national team. Ancestral diversity of players may lead to a lack of team spirit on the one hand but, on the other hand, may lead to better complementarity among players. It is well known that some football-specific skills (e.g., endurance capacity, muscle performance, height, or technical skills) are related to ancestral background (see Lippi et al., 2010). Therefore, ancestral diversity boosts complementarities among players holding different positions on the football team. Our findings establish a positive causal relationship between this measure of team diversity and team performance. We show that diversity benefits teams beyond any effect stemming from population size, GDP per capita, coach experience, and other factors. The result is quite significant and not negligible. Analyzed using various perspectives and considering endogeneity and measurement error concerns via an instrumentation method, the overall evidence produced in our specifications strongly suggests that diversity enhances performance at the match level as proxied by the goal difference.

Our study is not intended to be a biological one. We examine the effect on performance today of values and traits shaped across generations. Differences in these characteristics and their associated information, proxied by ancestral distances, cannot be captured (or measured) by simple country-fixed effects or other cultural and institutional characteristics. It is important to stress that our results do not carry any implications in terms of superiority or inferiority of particular ancestral information of specific origins over other ones. Rather, our interest is on the inherited diversity among the players on a team and how these differences translate into a comparative advantage at the *team level* in sportive performance.

Our work highlights a less evident yet relevant effect of mixing populations worldwide due to international migration. The results of these population movements have attracted an impressive amount of economic literature interested in migration's economic and cultural effects in the destination and origin countries. Further research in this field shall extend our analysis to larger geographical areas and other sports played collectively.

8. Tables

In this section, we gather the main tables of the paper. Additional tables are gathered in the following Appendix and in the Online Appendix.

Table 4
Probability of winning and ancestral diversity.

	Dependent variable: goal difference							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Variable of interest								
Bilateral diversity	0.018*	0.004	0.004	0.002	0.203**	0.339**	0.282**	0.283*
	(0.009)	(0.009)	(0.009)	(0.012)	(0.062)	(0.113)	(0.088)	(0.165)
Log of GDP/capita, home		-0.001	-0.002	0.013		0.025	0.010	0.010
		(0.046)	(0.046)	(0.070)		(0.057)	(0.053)	(0.077)
Log of GDP/capita, away		0.073*	0.071*	0.122**		0.016	0.036	0.105
		(0.043)	(0.043)	(0.061)		(0.062)	(0.055)	(0.078)
Log immig. stocks, 18y lag, home		0.010	0.010	0.006		0.030**	0.032**	0.032
		(0.010)	(0.010)	(0.015)		(0.013)	(0.013)	(0.023)
Log immig. stocks, 18y lag, away		-0.013	-0.013	-0.002		-0.026**	-0.030**	-0.018
		(0.009)	(0.009)	(0.013)		(0.012)	(0.011)	(0.017)
Population (mln), home			-0.000	0.000			0.001	0.002
			(0.001)	(0.001)			(0.001)	(0.001)
Population (mln), away			-0.000	-0.001			-0.001*	-0.002*
			(0.001)	(0.001)			(0.001)	(0.001)
Observations	3877	3568	3568	2832	3877	3568	3568	2832
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					51.57	22.32	33.24	9.76
Team FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes		Yes	Yes	Yes
Geo-political controls			Yes				Yes	
Pair FE				Yes				Yes

Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970-2018 (for columns 1 and 5) / years 1978-2018 (for all other columns). Dependent variable: Match outcome, equal 0 if home team loses, 0.5 for a tie and 1 for a victory. OLS results appear on the left (columns 1 to 4). Column 5 to Column 8 display IV results. The first 3 columns of OLS and IV include individual team and year fixed effects, as well as a stage dummy Columns 4 and 8 replace individual-team with pair fixed effects. Standard errors are clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F-test for weak instruments. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Table 5
Football performance and ancestral diversity of national teams: unilateral estimations.

	Dependent variable: change in rating of national football team (Elo score)							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Variable of interest								
Diversity	2.841**	2.596**	2.715**	2.515*	23.588**	22.058**	24.948**	33.813**
	(1.140)	(1.147)	(1.111)	(1.371)	(11.230)	(10.923)	(12.272)	(17.191)
Control variables								
Stand. dev. appearances		0.275***	0.276***	0.310***		0.292***	0.294***	0.320***
		(0.023)	(0.023)	(0.028)		(0.026)	(0.027)	(0.032)
Log of GDP/capita			8.707	9.638			17.870**	16.335*
			(6.494)	(7.759)			(8.070)	(9.096)
Population (mln)			0.324				0.145	
			(0.208)				(0.420)	
Log immig. stocks, 18y lag				-0.520				1.372
				(1.373)				(1.799)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					18.70	18.66	16.80	11.02
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Baseline estimates for the unilateral framework. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3, 5–7) / years 1978–2018 (in columns 4 and 8). Dependent variable: changes in the Elo score of the national team (end vs. beginning of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display OLS results, with heteroskedastic robust standard errors in parentheses, clustered at team level. Columns 5–8 display IV results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Table 6
Performance and diversity: controlling for initial strength.

	Dependent variable: goal difference							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Variable of interest								
Bilateral diversity	0.081* (0.041)	0.023 (0.040)	0.021 (0.040)	0.029 (0.053)	0.658** (0.284)	1.425** (0.499)	1.244** (0.397)	1.595** (0.748)
Control variables								
Initial Elo score, home	0.002*** (0.000)	0.001** (0.000)	0.001** (0.000)	0.002** (0.000)	0.002*** (0.000)	0.001** (0.000)	0.001** (0.000)	0.002** (0.001)
Initial Elo score, away	-0.002*** (0.000)	-0.001** (0.000)	-0.001** (0.000)	-0.001** (0.000)	-0.002*** (0.000)	-0.001** (0.000)	-0.001** (0.000)	-0.002** (0.001)
Log of GDP/capita, home		0.036 (0.207)	0.068 (0.208)	0.084 (0.305)		0.177 (0.253)	0.151 (0.241)	0.110 (0.370)
Log of GDP/capita, away		-0.513** (0.217)	-0.507** (0.217)	-0.205 (0.302)		-0.765** (0.283)	-0.671** (0.262)	-0.324 (0.410)
Log immig. stocks, 18y lag, home		0.050 (0.043)	0.033 (0.045)	-0.005 (0.068)		0.121** (0.058)	0.116** (0.059)	0.127 (0.104)
Log immig. stocks, 18y lag, away		-0.080* (0.046)	-0.085* (0.047)	-0.039 (0.064)		-0.131** (0.057)	-0.155** (0.058)	-0.121 (0.086)
Population (mln), home			-0.004 (0.003)	-0.004 (0.004)			0.001 (0.004)	0.004 (0.007)
Population (mln), away			-0.001 (0.003)	-0.004 (0.004)			-0.007* (0.004)	-0.012* (0.006)
Observations	3877	3568	3568	2832	3877	3568	3568	2832
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					52.77	24.01	35.49	10.50
Team FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes		Yes	Yes	Yes
Geo-political controls			Yes				Yes	
Pair FE				Yes				Yes

Notes: Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970-2018 (for columns 1 and 5) / years 1978-2018 (for all other columns). Dependent variable: Goal difference. OLS results appear on the left (columns 1 to 4). Column 5 to Column 8 display IV results. The first 3 columns of OLS and IV include individual team and year fixed effects, as well as a stage dummy Columns 4 and 8 replace individual-team with pair fixed effects. Standard errors are clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F-test for weak instruments. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Table 7
Further results.

	Dependent variable: goal difference				hyperbolic sine	home score	goal difference
	(1) **IV:** Diversity, appearance	(2) **IV:** Diversity, SW	(3) **IV:** 22 years lag	(4) **IV:** Coach info	(5) **IV:** Goal difference, hyperbolic sine	(6) **IV:** Outcome: home score	(7) **IV:** Diversity, home vs. away
Variable of interest							
Bilateral diversity			1.052*** (0.292)	1.275** (0.403)	0.833*** (0.246)	0.727** (0.318)	
Bilateral diversity, appearance	1.457** (0.472)						
Bilateral diversity, SW		1.900** (0.664)					
Diversity, home							1.100** (0.471)
Diversity, away							-0.870** (0.425)

(*continued on next page*)

Table 7 (*continued*)

	Dependent variable: goal difference				hyperbolic sine	home score	goal difference
	(1) **IV:** Diversity, appearance	(2) **IV:** Diversity, SW	(3) **IV:** 22 years lag	(4) **IV:** Coach info	(5) **IV:** Goal difference, hyperbolic sine	(6) **IV:** Outcome: home score	(7) **IV:** Diversity, home vs. away
Control variables							
Log of GDP/capita, home	0.193	0.179	0.059	0.066	0.023	0.138	0.121
	(0.253)	(0.291)	(0.238)	(0.244)	(0.147)	(0.174)	(0.282)
Log of GDP/capita, away	-0.575**	-0.705**	-0.415*	-0.586**	-0.147	-0.626**	-0.597**
	(0.263)	(0.326)	(0.251)	(0.264)	(0.153)	(0.205)	(0.283)
Log immig. stocks, 18y lag, home	0.165**	0.203**	0.127**	0.144**	0.096**	0.061	0.160**
	(0.067)	(0.081)	(0.058)	(0.061)	(0.038)	(0.044)	(0.067)
Log immig. stocks, 18y lag, away	-0.211**	-0.223**	-0.163**	-0.173**	-0.108**	-0.099**	-0.174**
	(0.066)	(0.074)	(0.055)	(0.059)	(0.033)	(0.047)	(0.064)
Population (mln), home	-0.001	0.005	-0.001	0.002	0.002	-0.001	0.002
	(0.003)	(0.005)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)
Population (mln), away	-0.006	-0.011**	-0.005	-0.008*	-0.005**	-0.002	-0.007*
	(0.004)	(0.005)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Observations	3568	3568	3351	3568	3568	3568	3568
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	29.88	16.98	55.71	34.90	33.24	33.24	11.37
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs from the first year available for the instrument to 2018. Dependent variable: goal difference for columns 1–4 and 7, its hyperbolic sine transformation in Column 5 and the goals scored by the home team in Column 6. In all regressions, we include team and year fixed effects, as well as a stage dummy, comparably to column 3 and 7 of the baseline Table 3. Columns 1–7 display IV results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Table 8
Placebo: athletics and diversity.

	Placebo			
	(1) Total medals	(2) Total medals	(3) Gold medals	(4) Gold medals
Variable of interest				
Diversity	-0.223	-1.178	0.053	0.003
	(0.527)	(0.983)	(0.220)	(0.363)
Log of GDP/capita	-0.242	-0.318	-0.105	-0.051
	(0.352)	(0.446)	(0.157)	(0.196)
Population (mln)	0.172***	0.243***	0.057***	0.076***
	(0.031)	(0.048)	(0.012)	(0.017)
Stand. dev. appearances	0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Log immig. stocks, 18y lag		-0.069		-0.014
		(0.096)		(0.042)
Observations	1900	1676	1900	1676
Kleibergen-Paap LM test	16.20	7.07	16.20	7.07
Kleibergen-Paap F test	16.52	7.16	16.52	7.16
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Notes: Estimates for the placebo analysis. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1, 3) / years 1978–2018 (in columns 2, 4). Dependent variables from left to right: total medals in athletics; gold medals in athletics. In all regressions, we include team and year fixed effects, as well as a stage dummy. All columns display IV results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Declaration of competing interest

I declare that I have no relevant material financial interests that relate to the research described in this paper. This paper relies on data that were collected on the web and that we built ourselves. Other data were obtained from public sources and these sources are reported in the relevant sections.

Data availability

Data is stored in the github repository of Silvia Peracchi, and will be made available to the public at the following link: https://github.com/Sil-Per/Diversity_Performance_Replication_data.

Appendix A. Additional material

Table A9
Description of variables in the benchmark analysis.

Variable name	Variable description	Variable source
Performance measures		
Goal difference	Goals of team i *home* - Goals of team j. *away*	Mart Jürisoo
Goal difference, hyperbolic sine	Hyperbolic sine transformation of *Goal difference*	*see Goal difference*
Diversity measures		
Bilateral diversity	Diversity score of team i *home* - Diversity score of team j *away*. Benchmark measure, ancestral distances are based on dominant populations	Surname predictions: forebears.io. Ancestral distance measures: Spolaore and Wacziarg (2009)
Bilateral diversity, appearance	Diversity score of team i *home* - Diversity score of team j *away*. Alternative measure, weighted by minute appearances	As above
Bilateral diversity, SW	Diversity score of team i *home* - Diversity score of team j *away*. Alternative measure, based on weighted ancestral distances.	As above
Diversity, home (Diversity, away)	Diversity score of team i *home* (team j *away*)	As above
Team-level variables		
Stand. dev. squad age, home (Stand. dev. squad age, away)	Standard deviation of team i *home* (team j *away*) members' age	Constructed from squad-level data on worldfootball.net
Squad age, home (Squad age, away)	Average of team i *home* (team j *away*) members' age	As above
Squad age, squared, home (Squad age, squared, away)	Square of squad age, home (*away*)	As above
Stand. dev. appearances, home (Stand. dev. appearances, away)	Player turnover for team i *home* (team j *away*), as computed from the minute appearances	As above
Foreign coach, home (Foreign coach, away)	Dummy =1 if the team i *home* (team j *away*)'s manager is foreign	As above
Coach age, home (Coach age, away)	Age of team i *home* (team j *away*)'s coach (approximated), computed as year of championship minus year of birth	As above
Macroeconomic variables		
Population (mln), home (Population (mln), away)	Team i *home* (team j *away*)'s country population size (millions of units)	WDI, SP.POP.TOTL total population; Head et al. (2010)
Log of GDP/capita, home (log of GDP/capita, away)	Log of per capita GDP for team i *home* (team j *away*)'s country	UN Statistics Division: National Accounts Main Aggregates Database
Log immig. stocks, 18y lag, home (Log immig. stocks, 18y lag, away)	Log of the stocks of immigrants for team i *home* (team j *away*)'s country, lagged 18 years	WDI, International migrant stock (see Unilateral table for details.) Complemented with (Özden et al., 2011)
Adversary's strength, home (Adversary's strength, away)	Average Elo score level of the teams faced, measured at the beginning of the stage	Own computation from match-level data
Contiguity	Dummy =1 if the team i *home* and j *away*) share/ have shared historically a border	Spolaore and Wacziarg (2009)
Same nation	Dummy =1 if the team i *home* and j *away*) are/ have been historically part of the same nation	As above
Common language	Dummy =1 if the team i *home* and j *away*) share/ have shared historically an official language	As above
FIFA video game variables	Definition description is sourced by Electronic Arts website and can be retrieved at https://www.ea.com/en-gb/news/fifa-12-attributes-guide-02, Last accessed: June 2023	
Crossing	Accuracy of crosses (standard deviation)	Electronic Arts, FIFA, national teams' player attributes retrieved in March 2023 from https://sofifa.com.
Finishing	Accuracy of shooting from inside the box (standard deviation)	As above
Heading accuracy	Ability to get the head on the ball, accuracy of headed passes and headers at goal (standard deviation)	As above
Short passing	Accuracy and speed of passing over a short distance (standard deviation)	As above

(*continued on next page*)

Table A9 (*continued*)

Variable name	Variable description	Variable source
Volleys	Technique and accuracy of shots taken while the ball is in the air (standard deviation)	As above
Dribbling	Ability to keep possession of the ball while running with it (standard deviation)	As above
Curve	Effectiveness of curls to crosses, passes and shots (standard deviation)	As above
Long passing	Ability to pick out far-away teammates (standard deviation)	As above
FK accuracy	Free-kicks quality	As above
Ball control	Quality of controlling and keeping control of the ball (standard deviation)	As above
Acceleration	Time to reach top speed (standard deviation)	As above
Sprint Speed	Speed of sprints (standard deviation)	As above
Agility	Quality of acrobatic shots and clearances, dribbling ability (standard deviation)	As above
Reactions	Adaptation to contextual changes (standard deviation)	As above
Balance	Responsiveness (standard deviation)	As above

Table A10
Additional results: goals for, goals against.

	(1) **IV:** Poisson, control function	(2) **IV:** Poisson, control function	(3) **IV:** Poisson, control function	(4) **IV:** Poisson, control function
	Dependent variable: home team's goals scored			
AMEs diversity away	-0.227	-0.673***	-0.582***	-0.156
	(0.160)	(0.255)	(0.211)	(0.378)
AMEs diversity home	0.475***	0.665**	0.663**	0.937**
	(0.175)	(0.314)	(0.260)	(0.474)
	Dependent variable: away team's goals scored			
AMEs diversity away	0.433***	0.548**	0.405**	0.492
	(0.123)	(0.215)	(0.171)	(0.413)
AMEs diversity home	-0.211*	-0.579**	-0.493**	-1.462***
	(0.124)	(0.242)	(0.196)	(0.557)
Observations	3877	3568	3568	2510
Team FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes
Geo-political controls			Yes	
Pair FE				Yes

Notes: Average marginal effects, bootstrap estimates. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (column 1) / years 1978–2018 (in columns 2, 3, 4). Dependent variable: home team's number of goals scored in the top sub-table, away team's number of goals scored in the top sub-table. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display results from a Poisson, control-function regression, with 2000 bootstrap replications, clustered at the pair level. Bootstrap replications are mean-trimmed, with 10% tails trimming. Standard deviations are in brackets. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Additional results: goals for, goals against To accommodate the discrete and non-negative nature of the goals-scored outcomes, we use a count data model estimated by poisson pseudo-maximum likelihood. To account for endogeneity concerns, we use a control function approach (see for instance Lin and Wooldridge (2019) for a discussion of the relevance of this approach, and Miroudot and Rigo (2021) for an application of the technique to a gravity model setting). Table A10 presents average marginal effects of diversity on the two teams' outcomes considered separately. Our dependent variable is the number of goals made by the home team in one set of regressions and by the away team in a second set of regressions. We standardize our regressors of interest to simplify the interpretation of the partial effects and present average marginal effects (AME) in Table A10. We maintain the same sets of controls as the benchmark. The AME results suggest an effect broadly in line with our previous findings. As the top part of Table A10 displays, the diversity of the home team (respectively, away team) when the effect is significant and positively (respectively, negatively) affects its performance. The diversity of the opponent negatively affects it. The expected goal count increases from 0.475 to 0.94 for a given increase of a standard deviation increase in the home team diversity, while it decreases for a given increase of the away team diversity. Results are broadly similar in the away score specifications, shown at the bottom of Table A10. In both specifications, however, the addition of pair fixed effects diminishes the strenght of the role of diversity of the opposite team.

Appendix B. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2023.07.024.

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