Collaboration and Cultural Homophily in Global Teams

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Abstract

How do cultural barriers related to nationality, colonial legacy and language affect collaboration in multinational teams? We address this question by creating and exploiting an exhaustive dataset recording all 10.7 million passes by 7 thousand professional European football players from 132 countries fielded by all 154 teams competing in the top 5 men leagues over 8 sporting seasons, together with full information on players' and teams' characteristics. We use a discrete choice model of players' passing behavior as a baseline to separately identify collaboration due to biased cultural preferences ('choice homophily') from collaboration due to opportunities ('induced homophily'). The outcome we focus on is the 'pass rate', defined as the count of passes from a passer to a receiver relative the passer's total passes when both players are fielded together in a half-season. We find strong evidence of choice homophily. Relative to the baseline, player pairs of same culture have a 2.50 percent higher pass rate. Passes between players of same nationality and between players of same colonial legacy but different nationality are associated respectively with 3.01 and 2.34 percent higher pass rates. Speaking the same language without sharing the same nationality nor the same colonial legacy has a negligible effect. These findings show that choice homophily based on culture is pervasive even in teams of very high skill individuals with clear common objectives and aligned incentives, who are involved in interactive tasks that are well defined, readily monitored and not particularly language intensive.

Keywords: Organizations, teams, culture, homophily, diversity, language, globalization, border effect, big data, text as data, football

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1. Introduction

To compete in the global economy, companies are increasingly calling on a multinational workforce. As discussed, for instance, by Neeley (2015), this has pros and cons. On the one hand, a multinational workforce allows companies to build teams that offer the best expertise from around the world, and draw on the benefits of international diversity by bringing together people from many cultures with varied work experiences and perspectives. On the other hand, teams like these also face several hurdles. When team members have from different cultural background, communication can rapidly deteriorate, misunderstanding can ensue, and cooperation can degenerate into distrust.

In this paper we systematically investigate how barriers related to diversity in cultural background affect collaboration in multinational teams (Lazear, 1999*b*,*a*). We define 'collaboration' as the situation of two or more people working together to create or achieve the same thing (Cambridge Dictionary), and study teams that are not geographically dispersed, as is often the case in multinational companies, since dispersion may *per se* inhibit collaboration (Joshi et al., 2002). We characterize the cultural background (henceforth, simply 'culture') of team members in terms of a set of cultural traits (Spolaore and Wacziarg, 2016; Desmet and Ortuño-Ortín, 2017). These include language as well as norms, values and attitudes that are transmitted intergenerationally, which we proxy through nationality and colonial legacy. We show that a 'border effect' between team members of different culture may indeed hamper collaboration, pretty much as different language and colonial past hamper international trade in goods and services between the regions of different countries (Head and Mayer, 2014). Team members of same culture collaborate more than team members of different culture.

We base our investigation on the unique features of a newly assembled dataset recording all passes made by professional European football players in the top five men leagues (Premier League in England, Ligue 1 in France, Bundesliga in Germany, Serie A in Italy, La Liga in Spain) over eight sporting seasons (2011-12 to 2018-19) together with full information on players' and teams' characteristics as well as their performances.[1] The dataset records 10.7 million passes made in 14,608 games by 7,000 players from 132 countries fielded by 154 teams. Passes are aggregated by passer-receiver player pairs and half-seasons as these are time periods in which football clubs have stable squads. The analysis is then carried out on the resulting three-dimensional (unbalanced) panel of 669 thousand passer-receiver pairs over 16 half-seasons. We measure collaboration as the average number of passes per minute between a pair of players in a half-season (which we call their 'pass rate'), and study how it is affected by the pairs' nationalities, languages and colonial legacies. Passes are the essential building blocks of football. They represent how players work together for the common objective

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[1] With 'European football', or simply 'football' henceforth, we refer to 'association football', which is commonly known as 'football' in Europe and 'soccer' in the United States (Tovar, 2020) .

of scoring or preventing the opponent from scoring a goal. Importantly, passes are also positively correlated with winning more league points and achieving higher league standings.[2]

This type of sports data has several advantages. First, the European football industry is very globalized: fans are spread around the world, and multinational teams are the rule in the top five leagues.[3] Second, football players are very mobile internationally, and their mobility decisions are typically made for work-related reasons, with pay being the most prominent of them. Third, in the top five leagues players are very diverse in terms of origin as they come from over a hundred countries. At the same time, they are all very high skilled (and well-paid) workers hardly facing obstacles with integration outside the workplace. Moreover, while language may matter for collaboration, the role of language as a sheer means of communication rather than a broader cultural trait is unlikely to dominate as football tasks are not particularly language intensive (Nüesch and Haas, 2013). Fourth, all sorts of player as well as team characteristics and performance indicators are precisely measured, and fastidiously recorded. Moreover, extensive media coverage can be readily used to shed light on any odd data patterns. Fifth, while team composition is exogenous to players' decisions, collaboration with other team members is mostly up to their individual choices. Sixth, the 'rules of the game' are codified, and crystal clear to all players and teams, ruling out the possibility that players of any specific culture may collaborate more with one another only because they happen to have a better grasp of those rules than other players.

All these features allow us to investigate collaboration in competitive global teams of high skilled workers with precise common objectives, leveraging a big dataset on interactions in an actual workplace rather than in an artificial experimental lab (Jackson et al., 2003), while also exploiting an extremely rich set of team and worker controls. Moreover, the fact that all players are men allows us to analyze how cultural barriers affect collaboration in multinational teams separately from issues of gender diversity.[4]

We are not the first to exploit team sports data to analyze the potential gains and

[2]In our dataset, regressing points per game (in levels) on log total passes, team and league by half-season fixed effects and conditioning on league specific aggregate trends shows that, in a half-season when a team passes 10% more than its average pass frequency across half-seasons, it wins 0.025 points (or 2.1%) more than its average points across half-seasons. Over a typical league's season of 38 games, this sums up to 1 point (compared to an average of 50 points per team in a season). This difference is equivalent to one position difference in final standings. See Appendix D for details.

[3]On average teams in our sample have a squad of players from 13 countries and field a starting eleven with players from 6 countries.

[4]There is a growing literature investigating the influence of gender composition on group performance and decision making. See, e.g., Adams and Ferreira (2009) and Apesteguia et al. (2012) on how boardroom gender diversity relates to measures of corporate performance; Ahern and Dittmar (2012) Ahern and Dittmar (2012) and Matsa and Miller (2013) on how the introduction of gender quotas for directors affect firm value; Adams and Funk (2012) on how those findings may be explained not only by the different behavior of diverse boards but also by inputs into board behavior that vary with boardroom gender diversity.

losses from employing culturally diverse work teams. In the case of the top North American ice hockey league (National Hockey League), (Kahane et al., 2013) find that the presence of European players (with Europe being the typical origin of foreign players) does increase firm-level performance: teams that employ a higher proportion of European players perform better. However, their results also indicate that teams perform better when their European players come from the same country rather than being spread across many countries. When teams have players from a wide array of European countries, integration costs associated with language and cultural differences may start to override any gains from diversity. Parallel evidence based on European football leads to mixed conclusions. In the top German league multinational teams have been found to perform worse than teams with less national diversity (Nüesch and Haas, 2013), whereas the opposite has been found in the top continental tournament (Ingersoll et al., 2017). Studying the top leagues of England and Spain, Tovar (2020) suggests that conflicting results may derive from a hump-shaped relation between team performance and predominant nationality. This echoes (Kahane et al., 2013) in that an optimal degree of diversity may exist. What distinguishes our analysis from these and related works is that we zoom in on collaboration and we can measure it accurately through the pass data[5].

The key methodological challenge that our investigation faces has been highlighted in the studies on homophily, defined as the tendency to associate with similar others (Lawrence and Shah, 2020). That team members of same culture collaborate more than team members of different culture is a statement about homophily. It highlights common cultural traits as the antecedents of homophily, that is, the specific attributes that serve as its basis, while singling out collaboration as the targeted consequence of homophily (Ertug et al., 2021). In this respect, in studying homophilic behavior an important distinction has been made between two underlying mechanisms: opportunities and preferences (McPherson and Smith-Lovin, 1987; McPherson et al., 2001). According to the former mechanism, individuals' distributions across categories within a social context define the probability they choose similar others (Lawrence and Shah, 2020). This may mechanically 'induce' homophily, irrespective of whether players have any actual preference for similar others, and thus it may not tell much about their real tendency to associate with similar others. Lawrence and Shah (2020) offer the following simple example. Consider a group of 100 geoscientists who associate with one

[5]Beyond diversity, team sports data are increasingly used to study various issues in labor and public economics. For example, Parsons et al. (2011) exploit data from the top North American baseball league (Major League Baseball) on the way umpires judge throws by pitchers of different race/ethnicity to study discrimination and its impact on discriminated groups' behavior. Kleven et al. (2013) rely on data for professional football players in Europe to shed light on the international mobility responses of workers to tax rates and their impact on local labor markets. Arcidiacono et al. (2017) use data on the top North American basketball league (National Basketball Association) to assess whether worker compensation is influenced by productivity spillovers to coworkers. Gauriot and Page (2019) use European football data for the five top leagues to understand how workers' valuations may be affected by luck.

another during a conference workshop. If 40 percent are geochemists and 60 percent are hydrologists, the expected rate for geochemists associating with other geochemists is 0.40. Only when the proportion of geochemists' associations with other geochemists exceeds this baseline, it demonstrates a preference for geochemists to associate with other geochemists. It is this preference that distinguishes 'choice homophily' from 'induced homophily'.[6] Hence, to be of any interest at all, the statement that team members of same culture collaborate more has to be based on choice homophily after controlling for induced homophily.

Defining the baseline is quite straightforward in the previous example. It is much less so when individuals may or may not differ along several potential attributes that could confound the roles of the targeted antecedents of homophily, making it harder to ascertain whether individuals are mechanically induced to choose similar others. We address these identification issues by designing the baseline in terms of a discrete choice model of players' passing behavior. The model determines how the pass rate for a pair of players is pinned down by their characteristics and opportunities during the matches they play together in a given time period. It is implemented empirically by a Poisson regression with player characteristics as well as player-time fixed effects as controls. Results are then corroborated by a rich set of robustness checks.

We find strong evidence of choice homophily: players have a preference to pass more to players of their same culture than to other players. Specifically, the outcome we focus on is the 'pass rate' defined as the count of passes from a passer to a receiver relative the passer's total passes when both players are fielded together during a half-season. In a regression with passer by half-season fixed effects as well as receiver by half-season fixed effects, conditioning on pass features (such as length) shows that player pairs of same culture have a pass rate 2.50 percent higher than player pairs of different culture. Accordingly, sharing the same cultural background is about as likely to lead to more passes as doubling the player pair's valuation (a consensus measure of their skills). As for the different cultural traits, passes between players of same nationality, same colonial legacy and same language are associated respectively with a pass rate that is 3.01, 2.34 and 0.66 percent higher than the pass rate between players without shared language, shared colonial legacy and shared nationality. Choice homophily is more pronounced for complex pass sequences in which the ball goes back and forth between a given player pair. For these sequences, the pass rate for pairs of same culture is 5.0 percent higher than for pairs of different culture, compared with 2.1 percent for single passes. Shared experience does not affect these results: once individual experience is controlled for, shared experience is irrelevant. This suggests that culture does not simply capture knowing each other.

[6] In the sociological literature the tendency of people of different types to associate with similar others in excess of the baseline of their types' relative population sizes is also called 'inbreeding homophily' (e.g. Coleman (1958); Marsden (1987); McPherson et al. (2001). See also Currarini et al. (2009).

These findings show that homophily based on cultural traits is pervasive even in teams of very high skill individuals with clear common objectives and aligned incentives, and involved in interactive tasks that are well-defined and not particularly language intensive.

The rest of the paper is organized as follows. Section 2 offers a selective overview of the related literature beyond works already referenced in this introduction. Section 3 describes data collection and our dataset. Section 4 introduces the discrete choice model of passing behavior. Section 5 presents the model estimation, whose results are then discussed in Section 6. Section 7 concludes.

2. Related literature

This paper is related to various research streams of the vast literature on cultural diversity and performance in teams, which spans from management (see e.g. Earley and Mosakowski (2000) and (Jackson et al., 2003)) to education studies (see e.g. Terenzini et al. (2001)).

Four streams are particularly relevant to what we do. The first is concerned with 'diversity spillovers', which improve team performance in a diverse environment, but not necessarily in a team that is itself diverse (Ottaviano and Peri, 2006, 2005). This stream highlights four main mechanisms (Buchholz, 2021). Diversity increases productivity: (i) when people from different countries work on problems together, in turn identifying better solutions by combining their knowledge ('interactive problem-solving'), (ii) through increasing the specialization, variety of skills and approaches to tasks within an occupation, though without necessarily requiring interaction between people from different countries of birth ('complementary task specialization'), (iii) when people from the same country of birth cluster in particular occupations and this clustering facilitates stronger knowledge exchanges ('niching effects'), (iv) when simply through exposure to a diverse range of knowledge and approaches to problems workers learn and become more productive ('exposure effects'). The evidence on US Metropolitan Statistical Area reported in Buchholz (2021) supports exposure effects as the main mechanism, but also interactive problem-solving and complementary task specialization seem to play an important role.

This first stream does not leverage information on diversity and collaboration within teams, which is what we do. In this respect, our investigation is more closely related to a second research stream that studies how individuals of different ethnicities may complement each other in production, but workers of the same ethnic background may collaborate more effectively (Lazear, 1999*b*,*a*; Lang, 1986). Specifically related to our investigation are works highlighting how distortions due to ethnic diversity and discriminatory worker attitudes affect firms and their organization of production. These studies face stiff data challenges. To systematically examine the effects of culture and language within a firm, one needs a host of detailed data: the nationalities of all workers must be identifiable, each worker's skills and output, as well as the collective

output of the firm, must be measurable, and all other factors of production should be held constant (Kahane et al., 2013). That is why works on firms are typically based on field experiments (Bertrand and Duflo, 2017). For instance, Hjort (2014) studies team production at a plant in Kenya, where an upstream worker supplies and distributes flowers to two downstream workers, who assemble them into bunches. He finds that upstream workers undersupply non-coethnic downstream workers (vertical discrimination) and shift flowers from non-coethnic to coethnic downstream workers (horizontal discrimination), at the cost of lower own pay and total output. Team pay, whereby the two downstream workers are remunerated for their combined output, is shown to mitigate discrimination and its allocative distortions[7].

In Hjort (2014), the upstream worker's decision on distributing flowers to the downstream workers resembles the choice a football player faces on passing the ball to his teammates. The context is, however, quite different. Whereas a Kenyan plant is a low skilled, highly charged context in a developing country with ethnic conflicts, a European football team is a high skilled, lowly charged context in a developed area with no real conflicts. Moreover, the flower plant and the football team setups have different pros and cons. The former can exploit an essentially random rotation process to assign workers to positions for identification, but its external validity may be limited. In the latter setup rotation is arguably not random as it depends on the manager's choices, but the richness of information from which to obtain all sorts of individual and team controls makes the case for external validity stronger. Be it as it may, non-random rotation due to endogenous team formation leads to known biases. Calder-Wang et al. (2021) exploit a dataset of MBA students who participated in a required course to propose and start a real micro-business that allows them to examine horizontal diversity (i.e., within the team) as well as vertical diversity (i.e., team to faculty advisor) and their effect on performance. The course was run in multiple cohorts in otherwise identical formats except for the team formation mechanism used. In several cohorts, students were allowed to choose their teams among students in their section. In other cohorts, students were randomly assigned to teams based on a computer algorithm. In the cohorts that were allowed to choose, Calder-Wang et al. (2021) find strong selection based on shared attributes. Among the randomly-assigned teams, greater diversity along the intersection of gender and race/ethnicity significantly reduced performance. However, the negative effect of this diversity is alleviated in cohorts in which teams are endogenously formed. In this respect, as long as the manager of a football team acts as mediator allowing the team to internalize the effects of diversity, the negative impact of diversity on collaboration we find can be seen as a lower bound estimate.

The third research stream analyzes homophily in scientific publications. Looking

[7]Conflicts exacerbate discrimination. Hjort (2014) finds that a period of ethnic conflict following Kenya's 2007 election led to a sharp increase in discrimination at the flower plant. Using data from GitHub on collaborative efforts in coding, the world's largest hosting platform for software projects, Laurentsyeva (2019) finds that political conflict that burst out between Russia and Ukraine reduced online cooperation between Russian and Ukrainian programmers.

into scientific papers written by US-based authors from 1985 to 2008, Freeman and Huang (2015) find evidence of choice homophily as persons of similar ethnicity co-author together more frequently than predicted by their proportion among authors; and that greater homophily is associated with publication in lower impact journals and with fewer citations, even holding fixed the authors' previous publishing performance. By contrast, diversity in inputs by author ethnicity, location, and references leads to greater contributions to science as measured by impact factors and citations. In the same vein, AlShebli et al. (2018) study the relationship between research impact and five classes of diversity: ethnicity, discipline, gender, affiliation, and academic age. Using randomized baseline models, they establish the presence of homophily in ethnicity, gender and affiliation. However, ethnic diversity has the strongest correlation with scientific impact. To further isolate the effects of ethnic diversity, they use randomized baseline models and again find a clear link between diversity and impact. Differently from these studies, we use a discrete choice model rather than randomized models to separate choice homophily from induced homophily.

Finally, the fourth research stream is concerned with the formation of social networks (Jackson, 2008). In particular, Currarini et al. (2009) and Currarini et al. (2010) study friendship formation in US schools when students have types (ethnicities) and may see type-dependent benefits from friendships. They show that any baseline matching process such that types are matched in frequencies in proportion to their relative stocks cannot replicate the homophily they observe in their data. On the contrary, a static model with both type-sensitive preferences ('choosing friends') and a matching bias ('meeting friends through friends') generates the observed patterns of homophily. Differently from these studies, our baseline is derived from a discrete choice model in which forward-looking behavior allows us to highlight the role of biased preferences ('passing to teammates') after netting out also the implications of biased meeting rates ('passing to teammates through teammates') through the model's structure and the dataset's richness.

3. Data

In this section we describe the scope of the unique data we use and briefly summarize how the data was collected, cleaned and transformed for the purpose of our analysis. After an overview, we separately describe the players' data, the data on passing events, and the combined dataset used for the model estimation.

3.1. Overview

To estimate how homophily may affect collaboration we collected, curated and cleaned a large set of raw data covering events such as passes and player characteristics. Data have been collected by webscraping using algorithms that extract information from websites. The output of these algorithms is structured text, which we transformed into tabular data with each observation being an event or a player.

The resulting combined dataset consists of all passes made by professional European football players in the top five men leagues over eight sporting seasons, together with full information on players' and teams' characteristics as well as their performances. It is a relational dataset linked via player names and additional information[8].

The top five leagues are the German Bundesliga, the French Ligue 1, the Spanish La Liga, the English Premier League, and the Italian Serie A. We have selected these leagues because of their undisputed reputation as the pinnacle of national football competitions. Moreover, data availability is the most comprehensive for these leagues.

The dataset covers all games played in the sporting seasons from 2011-12 to 2018-19, for which data quality is the highest and predate the COVID-19 pandemic. A season is the time period between mid-August to mid-May, during which each team plays twice (home and away) with every other team in its league.

A season is composed of two halves: the Fall half-season runs from mid-August till the end of December, the Winter-Spring runs till mid-May. Exact cutoff dates vary by leagues. The Premier League, La Liga, Serie A and Ligue 1 are all composed of 20 teams (playing 20×19=380 games), while there are 18 teams (18×17=306 games) in the Bundesliga. In any given season, there are 98 teams in our sample, and we have 98x16=1568 team by half-season units in our dataset. Due to relegation and promotion, we have a total of 154 teams in the sample. Overall, our dataset covers a total of 8×(380×4+306)=14,608 games.[9]

3.2. Player dataset

The information on players and their characteristics are compiled by Transfermarkt[10]. For every player, data include his country of birth, single or multiple citizenship information, country of birth, date of birth, height, and participation in a national team. These are all time-invariant in our dataset. They also include a player's estimated transfer value, that is, the "expected value of a player in a free market" as determined by a group of experts. This estimate is based on how much a player may contribute to the team's success, how well he plays, how valuable he may be to another team. As such, a player's transfer value is considered a consensus measure of the quality of his football skills. Transfer values are estimated twice a year in correspondence with the transfer windows.

We have 6,998 players in our sample, for whom we can fully map their entire career, with a typical team relying on a squad of about 30 players.

European football is truly globalized as there are players from 132 countries of citizenship in our sample. French, Spanish and Italian players make up the largest citizenship groups, followed by Germans, English, Brazilians and Argentinians. Other

[8]See replication options in Appendix E.

[9]Data quality and coverage are both very high in our datasets. Nevertheless, a few small data cleaning steps were needed and we discuss these issues discussed in Appendix B

[10]See https://www.transfermarkt.com/

countries of citizenship with several players include the Netherlands, Serbia, Senegal, and Uruguay. Table 1 reports the share of countries in terms of first citizenship of players, for countries with at least a 1% share.

Table 1: Most frequent nationalities

Country	share (%, all players)
Spain	13.5
France	12.0
Italy	9.8
Germany	8.4
England	7.0
Brazil	4.4
Argentina	3.4
Portugal	1.8
Netherlands	1.6
Senegal	1.6
Belgium	1.3
Serbia	1.2
Uruguay	1.2
Switzerland	1.2
Cote d'Ivoire	1.1
Croatia	1.1
Morocco	1.0
Denmark	1.0

Player level dataset, frequency of first citizenships. List of countries with at least a 1% share.

To determine whether two players have the same culture, we consider three cultural traits: nationality, language and colonial legacy.

First, nationality is defined based on citizenship of a country. As some players have multiple citizenships, we define two players as co-national if they share at least one of them, or have the same country of birth.

Second, for language we rely on CEPII data as in Head and Mayer (2014) to ascertain whether or not two countries share one or more common languages. For example, the official and widely spoken languages in Morocco are Arabic and French. Accordingly, players from Morocco and Egypt share Arabic, those from Morocco and France share French, while those from Egypt and France do not share any language. We then assume that a player speaks (as mother tongues) the official and widely spoken languages of his country of citizenship at the beginning of his career (so a Moroccan player speaks Arabic and French). Hence, a player starting his career in Morocco shares a common language with players starting their careers in Egypt or France, whereas a player starting his

career in Egypt (France) shares a common language with players starting their careers in Morocco but not with those starting their careers in France (Egypt). We consider some languages that are very close, even if not identical as one language (See Appendix B.1 for details.

Third, to ascertain common colonial legacy, we use colonial links data from CEPII as Head and Mayer (2014). For some players (such as South American and Spanish, Brazilian and Portuguese, French and Senegalese) same colonial legacy subsumes same language. Other players (such as Belgian and Canadian, German and Austrian) share the same language but do not share the same colonial legacy.

We employed a "topcoding" principle: checking nationality first, colonial legacy second, and language third. Thus, based on nationality, language and colonial legacy, we defined the following categories:

1. Same nationality (e.g. two Argentinian players)
2. Same colonial legacy: different nationality, but same colonial legacy (e.g. Argentina and Spain, England and Egypt)
3. Same language: different nationality, different colonial legacy, but same language (e.g. Belgium and France)
4. No shared culture: different nationality, different colonial legacy and different language (e.g. Argentina and France).

More than quarter of players have multiple citizenship. In such cases, if two players are citizens of the same country or of at least two different countries with common language, they are considered as speaking the same language. Analogously, if two players are citizens of the same country or of at least two different countries with common colonial legacy, they are considered as having the same colonial legacy. More on how this is handled, see Appendix B.1.

In our dataset, 37.8% of the players have the same nationality, 8.0% have the same colonial legacy but different nationality, and 4.1% have the same language but different colonial legacy and different nationality. We consider all these players as having the same culture. According to this definition, 49.9% of the players in our sample have the same culture, whereas 50.1% of them do not.

3.3. Event feed and pass dataset

Information on passes comes from OPTA, a sports technology company, and is available via third party sites such as `whoscored.com`. OPTA's data are generated by people watching games and coding events helped by cameras. Events are recorded one-by-one and cross-checked to create highly reliable and widely used depictions of games. This is called the "event feed data". Our event dataset has been scraped from a third party website.

A pass is an event defined as "any pass attempted from one player to another",

including free kicks, corners, throw-ins, goal assists[11]. The event feed data include a timestamp, team id, x and y coordinates of where the pass took place in the pitch, and its outcome (e.g., a flag for a successful pass). Using the next event, the receiver and his coordinates can be recovered. We filtered the event feed data on successful passes only (i.e. those received by a teammate of the passer).

A row in the resulting passes dataset has the following key columns: passer/receiver ID, his team ID, position information on the pass, time into the game, nature of the pass. There are 17 passes per minute, on average, and there are about 800 successful passes on average per game, so we have 10.73 million passes.

We have aggregated the passes data to single games to generate variables such as the sum of passes between any two players in a game. We have then further aggregated these observations by half-season. The partition in half-seasons is suggested by the timing of the transfer windows, which are located between seasons (summer transfer window) and at the beginning of the calendar year (winter transfer window). It also splits the number of games during a season into two approximately equal parts: the number of games per team in a half-season ranges between 16 and 20 compared with the exact equal split of 17 for the German Bundesliga and 19 for the other top five leagues.

Under the reasonable assumption that, if two players never pass to each other during a half-season, it must be that it is impossible for them to do so due to fielding or positioning reasons (e.g. the two players are only fielded to substitute each other as forwards), we drop the corresponding player pairs from the dataset. However, if we observe that a player passes to a given teammate but is never reciprocated, we keep the player pair. This implies that we have some zeros in the dataset recording the lack of passes from a player to a teammate from whom he nonetheless receives passes. Only 7.8% of the observations give rise to such zeros.

As regards aggregation, half-seasons have several advantages compared to games. In a single game, two players may not play together for various reasons as squads are large and only eleven players can be fielded at the same time. This may raise a selection issue, which can be tackled by considering all the games in a season instead. If two players never pass to each other during an entire season, either they are never fielded together or one can safely assume they are never fielded in positions that interact. Moreover, considering a half-season allows one to investigate the role of common experience as players who spend more time together on the pitch may learn to pass more to each other. Half-seasons have also advantages compared to seasons. The presence of the winter transfer window implies that during a season a team's squad may change composition. Our assumption of unchanged player quality makes more sense in a half-season than in a season, especially as younger players may evolve. In this respect, half-seasons strike a balance between mitigating the selection issue and keeping squad composition fixed.

[11] See https://www.statsperform.com/opta-event-definitions.

Table 2: Variable types - based on level of aggregation

player specific	player-pair specific	half-season specific	Example variables	N
yes	-	-	player height, year of birth, nationality	6,998
yes	-	yes	players age, value, team id, half-season id, experience with the team	37,026
-	yes	-	player-pair's shared nationality indicator	310,493
-	yes	yes	player-pair's number of passes in half-season, shared experience with club	669,025

Estimation dataset. N refers to the number of different values, ie there are 7 thousand different players and 669 thousand different passer-receiver pair observed in a half-seasons.

Moreover, the fact that half-seasons are separated by transfer windows allows us to cleanly map players' careers as they change teams, thereby combining player and pass information in a consistent way.

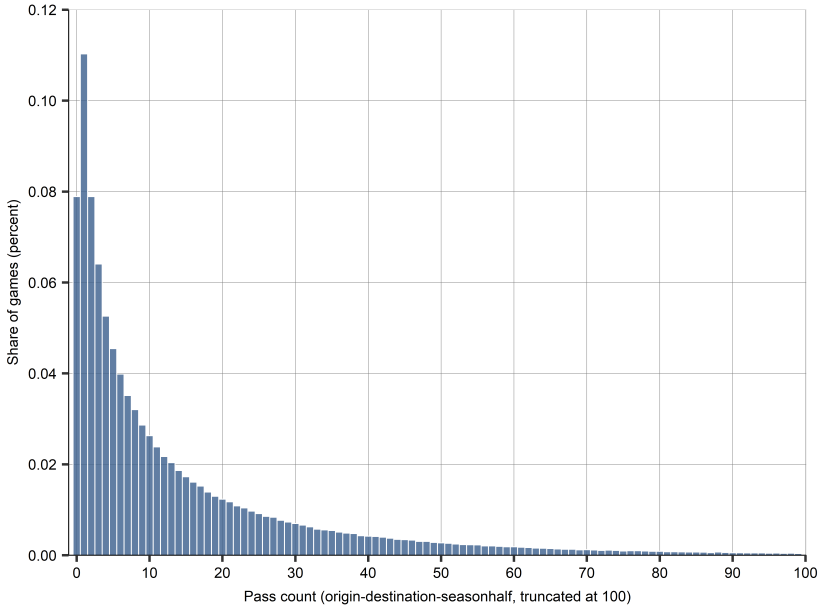
3.4. Combined dataset

The final task to prepare our estimation dataset is to combine player information and pass information. To match player and pass data, we had to identify players in both datasets and create a unique identifier for players. This process has proved to be a difficult task. First, there are players who are recorded differently across datasets - especially when their names have diacritical marks (such as "é"), are translated from a non-Latin alphabet, or include many middle names. Second, different players may have the same name, especially with frequent family names. To solve this issues, we developed a matching algorithm based on player names and additional information. The procedure is detailed in Appendix B.[12] Variables are aggregated at different levels, as shown in Table 2.

The resulting estimation dataset is a directional pass dataset that, keeping track of who is the passer and who is the receiver, consists of 669,025 observations at the passer, receiver and half-season level. In a half-season, a player makes a total of 650 passes on average (ranging between 2 and 3750, with median equal to 570). On average, he passes to 19.31 receivers (ranging from 2 to 35 with median equal to 20). The average pass count from passer to receiver is 15.92 (ranging from 0 to 488 with median equal to 8). The distribution looks highly skewed to the right as shown in Figure 1 where the distribution is truncated at 100 (98.63% of observations) for better visibility.

[12]We have also made a few decisions regarding data cleaning, dropping players who only had a single passing partner or those we could not identify (see B for details. All results are robust to these decisions.

Figure 1: Distribution of passes



4. A Discrete Choice Model of Passing Behavior

A crucial challenge in assessing how common culture affects collaboration through passes arises from the conflation of choice and opportunity. As discussed in the introduction, individuals may collaborate more with similar others because they choose to do so ('choice homophily') or because collaboration with similar others is forced on them by circumstances ('induced homophily'). In this section we develop a discrete choice dynamic programming model to help us disentangle choice from opportunity in an internally consistent way by controlling for observable player characteristics (such as team, position, valuation, citizenship) and pass features (such as average distance).[13]

Consider a football team of $N = 11$ players, indexed from 1 to N, engaged in a half-season consisting of P passing episodes.[14] During the half-season each player is assigned to a particular position on the pitch, which implies that a player's index identifies both his name and his position. Let us focus on two players, labeled o and d, and on the subset of passing episodes $T^{o,d}$ in which both players are on the pitch with player o having ball possession. A 'pass' from o to d is defined as a movement of

[13] See Keane and Wolpin (2009), Todd and Wolpin (2010) and Keane et al. (2011) for surveys of applications of dynamic programming models of discrete choice in labor economics and other applied microeconomic fields

[14] The model could be extended to allow for a squad of $N > 11$ players and different selections of players fielded during a half-season. Such extension, however, would not alter the model's insights informing our empirical analysis.

the ball determined by a decision made by player o ('passer') to kick or throw the ball to teammate d ('receiver'). For $d = o$ the passer keeps possession of the ball. We are interested in characterizing the probability that player o passes to player d rather than to any of the other nine teammates.

A passing episode consists of two periods: when the pass is initiated by o (t) and when the pass is received by d ($t+1$). The passer wants to maximize team payoff and understands that the benefit for the team of one of its players controlling the ball is determined by the ability and position of that player, and by some randomness due to the vagaries of the game. These may include, for instance, the performance of the opposing team, the referee's decisions or the weather conditions. We use $\ln u_t^d$ to denote the deterministic part of the team's benefit as determined by player d's characteristics, and z_t^d to denote the realization of its random part ('shock') due to match contingencies. Specifically, for each receiver d, z_t^d is the realization of a random variable Z with continuous differentiable c.d.f. $\Pr[Z \leq z] = G(z)$ over the support $(-\infty, +\infty)$. Passer o also understands the challenges he faces in passing the ball to receiver d. We call $\widetilde{c}^{o,d}$ the associated 'passing cost' capturing such challenges in terms of physical and mental effort. In particular, this cost may be high if the pass is difficult due to the positions of players and their reciprocal distance or o and d find it hard to collaborate due to different cultural traits. Finally, passer o realizes the difficulty receiver d may face in taking control of the ball, which depends on the receiver's characteristics. We use φ^d to denote the probability that receiver d takes control of the ball. We call this the probability of a successful pass. Hence, any difference in outcomes across the $T^{o,d}$ passing episodes ultimately depends on different success of attempted passes and different realizations of the shock due to match contingencies.

The passer's decision can be characterized as the problem of passing the ball to the receiver who generates the highest expected benefit for the team. The value function of this problem is written recursively as

$$U_t^o = \ln u_t^o + \max_{\{d\}_{d=0}^N} \left\{ \beta \varphi^d E\left[U_{t+1}^d\right] - \widetilde{c}^{o,d} + z_t^d \right\} \tag{1}$$

where the team's benefit U_t^o of controlling the ball in period t is split into two components: the benefit of player o currently controlling the ball (e.g. in the current period the player could try to score a goal; or he could decide to kick the ball out of play to allow the team to reorganize) and the option value of player o passing (or keeping control of) the ball at the beginning of the future period. These two components correspond to $\ln u_t^o$ and $\max_{\{d\}_{d=0}^N} \left\{ \beta \varphi^d E\left[U_{j+1}^d\right] - \widetilde{c}^{o,d} + z_t^d \right\}$ respectively, with expectation $E\left[U_{t+1}^d\right]$ taken over the realizations z_t^d of the shock. The parameter $\beta \in [0,1]$ measures the relative importance the team attaches to passing in general, independently from the specific passing episode. This is an important characteristic of the team's style of play. For example, low β would be associated with teams that try to score goals by quickly moving the ball into scoring range by long passes, through balls or long air balls, whereas high β would refer to teams that prefer to play less quickly, using many

short passes (also sideways or backwards) to find a weakness in the opposing team's tactics.

We assume that the random variable Z follows the Gumbel distribution (Type-I Extreme Value distribution)

$$G(z) = \exp\left(-\exp(-\kappa z)\right)$$

with mode 0 and concentration around the mode inversely related to $\kappa > 0$. Zero mode implies that there is no systematic deviation from the deterministic part of the team's benefit across players' assessments of match contingencies. As all players share the same κ, this is a team characteristic: players are trained to assess match contingencies in a common way. Smaller κ then implies more intense training to reduce variation in their individual assessments. The Gumbel assumption leads to a simple expression for the probability of player o passing to teammate d in period t. Specifically, after having taken expectations on both sides of (1), defining $V_t^o \equiv \exp E[U_{t+1}^o]$ and $c^{o,d} = \exp \widetilde{c}^{o,d}$ allows one to express the *ex ante* probability that player o in possession of the ball in period t successfully passes to teammate d at the beginning of period $t+1$ as

$$\pi_t^{o,d} = \left(V_{t+1}^d\right)^{\kappa\beta\varphi^d} \left(c^{o,d}\right)^{-\kappa} \left(\Lambda_{t+1}^o\right)^{-\kappa} \text{ with } \Lambda_{t+1}^o \equiv \left[\sum_{s=1}^{N} \left(V_{t+1}^s\right)^{\kappa\beta\varphi^s} \left(c^{o,s}\right)^{-\kappa}\right]^{\frac{1}{\kappa}}, \qquad (2)$$

which *ex post* becomes (approximately) the average share of successful passes that player o makes to player d per episode over a half-season in the subset of passing episodes $T^{o,d}$ when both o and d are fielded and player o has ball possession.[15] The probability that player o successfully passes the ball to player d in period t is thus determined by the team's expected benefit from player d controlling the ball in period $t+1$ (V_{t+1}^d), his probability of taking control of the ball (φ^d) and the difficulty of passing the ball to him ($c^{o,d}$), relative to the team's average benefit from its players $s = 1, ..., N$ controlling the ball in period $t+1$ (V_{t+1}^s), weighted by their probability of taking control of the ball (φ^s) and the difficulty of passing the ball to them ($c^{o,s}$).

In the data we observe the total number of team passing episodes (P), the number of passing episodes involving a pass from o to d ($P^{o,d}$), and the number of passing episodes when both o and d are fielded and player o has ball possession ($T^{o,d}$) over a half-season. If we define the half-season 'pass rate' as $p^{o.d} = P^{o,d}/P$, the model then implies $p^{o,d} = T^{o,d}\pi_t^{o,d}/P$, and thus

$$\log p^{o,d} = \log T^{o,d} + \log\left(\Lambda_{t+1}^o\right)^{-\kappa} + \log\left(V_{t+1}^d\right)^{\kappa\beta\varphi^d} + \log\left(c^{o,d}\right)^{-\kappa} - \log P. \qquad (3)$$

The distinction between distance and culture related challenges in passing from player o to player d embedded in $c^{o,d}$ can be made explicit by specifying the bilateral passing

[15] The fact that also $s = o$ is included in the sum $\sum_{s=1}^{N} \left(V_{t+1}^s\right)^{\kappa\varphi^s} \left(c^{o,s}\right)^{-\kappa}$ implies $\sum_{s=1}^{N} \pi_t^{o,s} = 1$.

cost multiplicatively as

$$c^{o,d} = \left(g^{o,d}\right)^{\gamma} \left(l^{o,d}\right)^{\lambda} \tag{4}$$

In (4) $g^{o,d}$ is the physical distance between the two players' positions so that $\left(g^{o,d}\right)^{\gamma}$ captures all distance-related frictions that make it difficult to pass the ball from passer o to receiver d independently of their identities. The term $\left(l^{o,d}\right)^{\lambda}$ captures, instead, all non-distance-related frictions that make it difficult to pass the ball from passer o to receiver d independently of their positions. These may include, for instance, limited experience in playing together but, crucially, also different cultural traits.

Substituting (4) into (3) gives

$$\log p^{o,d} = \log T^{o,d} - \kappa \log \Lambda^{o}_{t+1} + \kappa\beta\varphi^{d} \log V^{d}_{t+1} - \kappa\gamma \log g^{o,d} - \kappa\lambda \log l^{o,d} - \log P \tag{5}$$

which we will use in the next sections as the theoretical basis to empirically investigate the relation between the pass rate $p^{o,d}$ and the cultural dimensions of $l^{o,d}$. Before proceeding, three remarks are in order. First, equation (5) distinguishes the role of biased preferences ('passing to teammates'), which work through $\log l^{o,d}$, from the implications of biased meeting rates ('passing to teammates through teammates'), which work through the forward looking terms $\log \Lambda^{o}_{t+1}$ and $\log V^{d}_{t+1}$. Second, such distinction allows us to argue that in (5) the cultural dimensions of $l^{o,d}$ determine choice homophily (i.e. biased preferences), while induced homophily is determined by all other terms on the right hand side of (5).[16] Third, equation (5) resembles what is called in international economics a 'gravity equation', which explains exports from a country of origin to a country of destination in terms of the countries' characteristics as well as distance- and non-distance-related trade frictions. In this respect, in (5) cultural differences hamper collaboration between teammates pretty much as a 'border effect' hampers international trade in goods and services between the regions of different countries (Head and Mayer, 2014).

5. Empirical Implementation of the Passing Model

The empirical implementation of our theoretical model requires a generalized linear estimator with a log link function. In such setup there is a large literature on the benefits of using a Poisson model rather than a log(count) model with a large number of fixed effects[17]. This approach is in line with best practices in the estimation of gravity

[16] The pass rate in equation (5) is conditional on players being in the team, and homophily may play a role in team composition. As long as this affects induced homophily, our model allows us to net it out.

[17] In this paper, we follow the procedure described in (Berge, 2018). As discussed by (Hinz et al., 2021), a drawback of fixed effect models in general is the incidental parameter bias: having several

equations through fixed effects Poisson Pseudo Maximum Likelihood estimation (FE-PPML) in international trade (see e.g. Fally (2015) and Santos-Silva and Tenreyro (2021)). Nonetheless, we also provide robustness checks with a log(count) model.

We map our theoretical model into a Poisson model as follows. We use the number of passes from player o to player d as dependent variable. We call it $pass\_count_{o,d,t}$, which corresponds to $P^{o,d}$ in the theoretical model. We then introduce an exposure variable for the total number of passes by o when both o and d are on the pitch, which we call $T_{o,d,t}$ and corresponds to $T^{o,d}$ in the theoretical model. The log of this exposure variable is handled as an offset variable by forcing its coefficient to be equal to 1. The total number of passes per team in a half-season (P in the theoretical model) is absorbed through team by half-season fixed effects. As the parameter β may depend on team and player characteristics that change over time (such as the position and style of players as well as team tactics), we rely on player characteristics and team fixed effects, or alternatively player fixed effects, to absorb its variation.

We capture distance-related frictions that make it difficult to pass the ball from o to d (i.e. $\left(g^{o,d}\right)^{\gamma}$ in the theoretical model) by constructing the following measure:

$$PassFric_{o,d,t} = \gamma_1 PassDist_{o,d,t} + \gamma_2 Forwardness_{o,d,t} + \eta Position_o Position_d$$

where in a half-season $PassDist_{o,d,t}$ is the average distance of passes between the two players, $Forwardness_{o,d,t}$ is the share of passes between the two players with a forward direction, and $Position_o Position_d$ is a dummy variable capturing the two players positions (such as defender, midfielder and forward). As we acknowledge that $PassDist_{o,d,t}$ and $Forwardness_{o,d,t}$ may actually be a mechanism rather than a confounder, we will show results with and without them. In all models we will have a set of dummies for each pair of passer and receiver broad positions (such as forward to defender) ($position_o position_d$).

As for the cultural aspect of non-distance-related frictions that make it difficult to pass the ball from passer o to receiver d independently of their positions, we measure cultural affinity through the time-invariant variable $SameCult_{o,d}$, which combines the categories described in Section 3.2: $SameNat_{o,d} = 1$ if o and d have the same nationality, and $SameNat_{o,d} = 0$ if they have different nationality; $SameCol_{o,d} = 1$ if o and d have the same colonial legacy but different nationality, and $SameCol_{o,d} = 0$ if they have different colonial legacy and different nationality; $SameLan_{o,d} = 1$ if o and d have the same language but different colonial legacy and different nationality. The benchmark therefore consists of pairs with different nationality, different colonial legacy and

nuisance parameters to estimate, the estimated coefficient of the variable of interest may be biased. FE-PPML estimates can manage this type of bias better than non-linear OLS (Santos-Silva and Tenreyro, 2021). While Weidner and Zylkin (2021) show that the Poisson model still leave some room for potential bias, with no double player fixed effects and a large number of observations, the bias should be small in our case. In an unreported robustness check using the algorithm developed by Weidner and Zylkin (2021), we have indeed found only a small bias.

different language.

We estimate four versions of the Poisson model. The first version features a variety of player characteristics as controls:

$$E(pass\_count_{o,d,t}|...) = exp(\delta SameCult_{o,d} + PassFric_{o,d,t} + \ln T_{o,d,t} + \sum_{j=o}^{d} (\eta_j value_{j,t} + \theta_j playerchar_{j,t})) \quad (6)$$

where $SameCult_{o,d}$ is the same culture indicator. An estimated δ larger than zero would reveal the presence of choice homophily as it would imply that, all the rest given, players with same culture pass more to each other than to players of different culture. Potential confounding factors associated with the two players $j = \{o, d\}$ are captured by player valuation ($value_{j,t}$) and other player characteristics ($playerchar_{j,t}$). These include age, height, time (in days) elapsed since joining the team, and a binary indicator for being on loan.[18] We also include position by half-season dummies, nationality by half-season dummies, and team by half-season dummies. The second version of the Poisson model differs from the first in that it captures the potential confounding factors associated with the two players through additional fixed effects rather than player valuation and other player characteristics:

$$E(pass\_count_{o,d,t}|...) = exp(\delta SameCult_{o,d} + PassFric_{o,d,t} + \ln T_{o,d,t} + \upsilon_{o,t} + \upsilon_{d,t}) \quad (7)$$

where $\upsilon_{o,t}$ and $\upsilon_{d,t}$ are player by half-season fixed effects.[19] The third version of the Poisson model differs from the first in that it considers the three components of the same culture indicator $SameCult_{o,d}$ separately:

$$E(pass\_count_{o,d,t}|...) = exp(\delta_1 SameNat_{o,d} + \delta_2 SameCol_{o,d} + \delta_3 SameLan_{o,d} + PassFric_{o,d,t} + \ln T_{o,d,t} + \sum_{j=o}^{d} (\eta_j value_{j,t} + \theta_j playerchar_{j,t})) \quad (8)$$

where estimated δ's larger than zero would reveal the presence of choice homophily based on the corresponding cultural aspects. Finally, the fourth version of the Poisson model differs from the second in that it considers the three components of the same culture indicator $SameCult_{o,d}$ separately:

$$E(pass\_count_{o,d,t}|...) = exp(\delta_1 SameNat_{o,d} + \delta_2 SameCol_{o,d} + \delta_3 SameLan_{o,d} + PassFric_{o,d,t} + \ln T_{o,o,t} + \upsilon_{o,t} + \upsilon_{o,t}) \quad (9)$$

[18] For additional details on loans see in Appendix, Section A.2.

[19] We cannot have passer by receiver fixed effect as sometimes used in the gravity equation literature because our variable of interest is time-invariant.

where estimated δ's larger than zero would again reveal the presence of choice homophily based on the corresponding cultural aspects. In all estimations standard errors are clustered at the passer level.[20]

6. Homophily in Collaboration

The presentation of our empirical findings is organized as follows. First, we highlight our main results. Second, we discuss some extensions and robustness checks. Third, we investigate whether homophily is particularly relevant for complex collaboration. Fourth and last, we look at moderating effects and heterogeneity.

6.1. Main results

To set the stage for our main estimation results, it is useful to have a preliminary look at how homophily affects passes without distinguishing between its choice and induced aspects. We do so by estimating the effect of $SameCult_{o,d}$ as an unconditional average difference within team and half-season in the following Poisson model:

$$E(pass\_count_{o,d,t}|...) = exp(\delta SameCult_{o,d} + \nu_{team,t}) \tag{10}$$

where $\nu_{team,t}$ is a team by half-season fixed effect. The corresponding results, reported in Column (1) of Table 3, offer clear unconditional evidence of homophily: players with same culture tend to pass 6.55% more to each other than to players with different culture. With an average of 15.98 passes between players in a half-seasons, this unconditional mean corresponds to an average difference of 1.05 passes.[21]

Columns (2) and (3) report the results for the estimation of equations (6) and (7) respectively. In both columns, by forcing the coefficient of $lnT_{o,d,t}$ to be equal to one, the effect of culture is estimated for the number of passes from the passer to the receiver relative to the former's total number of passes when both players are fielded together. Team by half-season fixed effects absorb the total number of team passing episodes (P in the theoretical model). They also absorb team and team by half-season characteristics such as history or current management. Column (2) shows that, after conditioning on player characteristics and pass features, player pairs of the same culture have a pass rate of 2.04% higher than player pairs of different culture. All player characteristics vary over time, valuations change every half-season, and team, position, citizenship fixed effects are interacted with time period fixed effects. Receiver valuation and age are positively related to the pass rate, whereas the passer's valuation is negatively related.

[20] A common alternative in light of the gravity literature is clustering at passer-receiver level. This lead to somewhat smaller standard errors. However, with hundreds of thousand observations, standard errors have limited meaning anyway.

[21] The estimate is conditional on players being in the team, and homophily may play a role in its composition. This affects induced homophily, which our model allows us to net out

Table 3: Baseline results

	pass_count		
	(1)	(2)	(3)
Same culture (any) (0/1)	0.0655***	0.0204***	0.0250***
	(0.0091)	(0.0038)	(0.0042)
Average length of passes (ln)		-0.6759***	-0.7944***
		(0.0077)	(0.0094)
Average forwardness Ind (0-1)		0.0066	0.0143
		(0.0077)	(0.0099)
Passer valuation (ln)		-0.0088***	
		(0.0008)	
Receiver valuation (ln)		0.0103***	
		(0.0015)	
Observations	669,025	668,985	668,108
Pseudo R^2	0.07818	0.74163	0.75930
team-half_season fixed effects	✓	✓	
passer_position-league_half_season fixed effects		✓	
receiver_position-league_half_season fixed effects		✓	
passer_nationality-league_half_season fixed effects		✓	
receiver_nationality-league_half_season fixed effects		✓	
passer_position-receiver_position D		✓	✓
passer-half_season fixed effects			✓
receiver-half_season fixed effects			✓

Poisson regression model. Standard errors, clustered at passer level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Top 5 soccer leagues, 8 seasons: 2011-2019. Half-season: 16-20 games before and after 1 January. Same cultural background is equality of either cultural aspect (language, colonial legacy or nationality). Player values are start of the half-season In column 1, additional controls are (for both players): height, age, time since with club (in days), binary if on loan. Total team pass count is captured via team *half-season fixed effects.

Also pass distance is negatively related to the pass rate (concurring with the gravity logic of our theoretical model), while forwardness is positively (though insignificantly) related. Comparing the estimated coefficients of same culture and players' valuations reveals that they are of comparable magnitudes: sharing the same cultural background is about as likely to lead to more passes as doubling the players' valuation (conditioning on other player characteristics). This suggests that choice homophily has a substantial effect on collaboration. Column (3) replaces observable player characteristics with time varying passer by half-season and receiver by half-season fixed effects. This allows player attributes to change over time. It also implies that the estimated coefficient of same culture is close to what would be the average of coefficients if estimated one by one for teams and time periods. The estimated coefficient of same culture is 2.50%. This is our preferred estimate of the 'homophily premium': all the rest given, on average players passes 2.50% more to teammates of same culture than to teammates of different culture.

Table 4 reports the results obtained by unbundling nationality, colonial legacy and language. Columns (1), (2) and (3) correspond to the analogous columns in Table 3. While same language with neither same nationality nor same colonial legacy significantly matters only for the unconditional results in Column (1), same nationality and same colonial legacy without same nationality significantly matter for the unconditional results in Columns (2) and (3) based on equations (6) and (9) respectively. Our preferred estimate in Column (3) implies homophily premia of 3.01% for same nationality and 2.34% for same colonial legacy without same nationality.

Note that there is a substantial heterogeneity in the colonial legacy estimate: the point estimate for player pairs from European countries that used be in the same polity are negative (USSR, Yugoslavia) and it is zero for countries of the British isles (Ireland, N. Ireland and countries of Great Britain).

6.2. Extensions and robustness

We now look at some extensions and robustness checks focusing on the estimates for our preferred model (7) as reported in Column (3) of Table 3. The corresponding results appear in Table 5.

As the average length and the average forwardness of passes may be a mechanism rather than a confounder, in Column (1) we exclude them from the regression. This exclusion has, however, only a marginal effect on the homophily coefficient estimate (2.45% vs 2.50%).

In Column (2), we control for additional potential confounders. First, we add a binary variable to capture when players' valuations are close to each other signaling similar player quality. This is motivated by the possibility of assortative matching. If quality were correlated with nationality, this could confound our estimated homophily. The variable equals one if relative passer-receiver valuations are below the median, and zero otherwise. Second, in the same vein, there may be some physical attribute that is somehow typical of players of a certain country but not of others. As we have

Table 4: Baseline results: culture detailed

	pass_count		
	(1)	(2)	(3)
Same nationality (0/1)	0.0799***	0.0238***	0.0301***
	(0.0102)	(0.0042)	(0.0048)
Same colonial legacy (0/1)	0.0140	0.0227***	0.0234***
	(0.0149)	(0.0058)	(0.0066)
Same language only (0/1)	0.0501**	0.0008	0.0066
	(0.0213)	(0.0089)	(0.0095)
Average length of passes (ln)		-0.6759***	-0.7944***
		(0.0077)	(0.0094)
Average forwardness Ind (0-1)		0.0066	0.0142
		(0.0077)	(0.0099)
Passer valuation (ln)		-0.0088***	
		(0.0008)	
Receiver valuation (ln)		0.0103***	
		(0.0015)	
Observations	669,025	668,985	668,108
Pseudo R^2	0.07835	0.74164	0.75930
team-half_season fixed effects	✓	✓	
passer_position-league_half_season fixed effects		✓	
receiver_position-league_half_season fixed effects		✓	
passer_nationality-league_half_season fixed effects		✓	
receiver_nationality-league_half_season fixed effects		✓	
passer_position-receiver_position D		✓	✓
passer-half_season fixed effects			✓
receiver-half_season fixed effects			✓

Poisson regression model. Standard errors, clustered at passer level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Top 5 soccer leagues, 8 seasons: 2011-2019. Half-season: 16-20 games before and after 1 January. Same cultural background is equality of either cultural aspect (language, colonial legacy or nationality). Player values are start of the half-season In column 1, additional controls are (for both players): height, age, time since with club (in days), binary if on loan. Total team pass count is captured via team *half-season fixed effects.

Table 5: Results on Robustness

	pass count			pass count (ln)	pass count
	(1)	(2)	(3)	(4)	(5)
	Poisson	Poisson	Poisson	OLS	Poisson
Same culture (any) (0/1)	0.0245***	0.0212***	0.0232***	0.0208***	0.0249***
	(0.0048)	(0.0042)	(0.0041)	(0.0034)	(0.0044)
Average length of passes (ln)		-0.7824***	-0.7861***	-0.2898***	-0.8143***
		(0.0094)	(0.0091)	(0.0059)	(0.0114)
Average forwardness Ind (0-1)		0.0113	-0.0027	0.2446***	0.2868***
		(0.0098)	(0.0099)	(0.0043)	(0.0115)
Shared experience (0/1)		0.0105*			
		(0.0056)			
Height difference (cm)		-0.0126***			
		(0.0004)			
Similar valuation (1/0)		-0.0008***			
		(0.0002)			
Both players EU+ (1/0)		0.0100			
		(0.0116)			
Passer total passes when together			1.140***	-0.1309***	
			(0.0048)	(0.0026)	
Observations	668,108	668,108	668,108	669,025	432,125
Pseudo R^2	0.74289	0.76073	0.76038	0.27589	0.71358
passer-half_season fixed effects	✓	✓	✓	✓	✓
receiver-half_season fixed effects	✓	✓	✓	✓	✓
passer_position-receiver_position D	✓	✓	✓	✓	✓

Column 1-3 Poisson, column 4 OLS regression model. Standard errors, clustered at passer level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Top 5 soccer leagues, 8 seasons: 2011-2019. Half-season: 16-20 games before and after 1 January. Same cultural background is equality of either cultural aspect (language, colonial legacy or nationality). Player values are start of the half-season Total team pass count is captured via team *half-season fixed effects. Both players EU+ reflect national regulations to play, see Appendix A.3. Similar valuation and height: both below/above median.

data on the height of all players, we control for the absolute height difference (in cm) between passer and receiver. Third, we condition on a regulatory aspect that restricts the fielding of players from non-EU countries with league-specific exemptions. Combing through these, we add a binary variable equal to one if passer and receiver are from the EU or other exempted countries, and zero otherwise.[22] Finally, we add a binary variable that captures shared club experience as shared experience could be hidden behind homophily. This variable equals one if the passer and the receiver spent at least a year at a club together, and zero otherwise.[23] While most of these additional variables are actually correlated with passes, they alter the baseline estimates of homophily only marginally (2.12% vs 2.50%).

In Column (3), we add the total number of passes when both players are on the pitch, that is, we do not restrict the exposure coefficient of $lnT_{o,d,t}$ to unity. The fact that the resulting estimate is larger than one reveals a more-than-proportional effect of total passes on the bilateral pass count. Nonetheless, the coefficient estimate for homophily hardly changes (2.32% vs 2.50%). We observe slightly more action (2.08% vs 2.50%) in Column (4) when we use the same variables as in Column (3) relying on OLS with $\ln passcount$ rather than Poisson estimation.

Finally, in Column (5), to check whether our results are driven by peculiar cases, we exclude observations when a player passes to a teammate but is never reciprocated in a half-season, when two players spend less than 45 minutes together in a half-seasons, and when either the passer or the receiver is a goalkeeper.[24] While the number of observations is reduced by 36%, the point estimate for homophily is essentially unchanged (2.49% vs 2.50%).

Parallel results for the same set of extensions and robustness checks when keeping nationality, colonial legacy and language distinct can be be found in Table .10 in Appendix C.

6.3. Complex collaboration

If same culture is helpful for collaboration in general, one would expect it to be even more so when collaboration is more 'complex'. In our setup, this implies that same culture should matter more for more complex passing patterns. To investigate whether this is indeed the case, we distinguish between single passes (in which player o passes to player d and the ball does not come back) and complex pass sequences (in which the ball goes back and forth between the two players at least once).[25] On average, player pairs carry out 16 passes per half-seasons. A vast majority, 87%, are

[22] For details, see Appendix A: 20% of player pairs have at least one restricted player.

[23] Results are robust to using the log number of days spent together instead.

[24] The goalkeeper is allowed to use also his hands to deal with the ball as long as he remains in his team's penalty box.

[25] We can identify pass sequences because our raw event data has timestamps that allow us to capture them.

single passes, but 13% are complex pass sequences. These sequences feature 3.54 passes on average and 50% of player pairs are involved in at least a complex pass sequence in our sample.[26] Conditional on having joined at least a complex pass sequence in a half-season, on average player pairs are involved in 3.85 complex pass sequences in that half-season.

In Table 6 we present the results from two regressions. For cleaner comparison, in Column (1) we re-estimate our baseline model using as dependent variable the number of pass sequences (not necessarily complex) involving a pass between two given players instead of the number of passes between them. As these numbers are highly correlated (0.99), the results are aligned with those in Column (3) of Table 3. In contrast, in Column (2) we re-estimate the baseline model using as dependent variable the number of complex pass sequences in which the two players are involved. The comparison between the two columns reveals that the homophily premium is more than twice as large for complex pass sequences: 5.01% in Column (2) compared to 2.09% in Column (1). This confirms that homophily is especially important for more complex collaboration.

Table 7 repeats the analysis unbundling nationality, colonial legacy and language. The estimated coefficients for same nationality and colonial legacy are again more than twice as large in Column (2) than in Column (1). Strikingly, while the role of same language is irrelevant in Column (1), it is important in Column (2), and of comparable magnitude to the coefficients of same nationality and same colonial legacy.

6.4. Moderating effects and heterogeneity

As suggested by a variety of studies in economics, management and psychology surveyed in Ertug et al. (2021), one can think of several potential moderator variables at the individual level. To learn more about their possible relevance, we look at the heterogeneity of the estimated average effect focusing on differences by minority and majority group,low and high status, and experience. Specifically, we create groups for potential moderators and interact each moderator variable with the same culture indicator. For all these comparisons, we consider the passer's characteristics.

Results are shown in Table 8. The fourth column reports the same culture coefficient estimates for each subgroup, along with some basic information about subgroups. The third column shows the relative frequencies in the dataset. The last column highlights whether the interaction terms are different from zero at the 5% significance level.

Consider first the minority-majority divide. Existing evidence shows that a shared cultural background may be more important for minority groups. For instance, Greenberg and Mollick (2017) argue that belonging to a minority group acts as a mediator variable increasing homophily. In our setup, we can think of players playing in their home league (e.g. Spanish players in La Liga or German players in Bundesliga) as

[26] A large share of players who spend significant time on the pitch but do not produce many complex pass sequences are goalkeepers. In modern football goalkeepers pass quite a lot, but rarely take part in complex sequences of passes.

Table 6: Pass sequences and complex pass sequences

	pass seq count sequences (1)	complex pass seq count (2)
Same culture (any) (0/1)	0.0209***	0.0501***
	(0.0039)	(0.0071)
Average length of passes (ln)	-0.7007***	-1.724***
	(0.0091)	(0.0140)
Average forwardness Ind (0-1)	0.0839***	-0.5174***
	(0.0102)	(0.0141)
Observations	668,108	644,533
Pseudo R^2	0.74590	0.55971
passer-half_season fixed effects	✓	✓
receiver-half_season fixed effects	✓	✓
passer_position-receiver_position D	✓	✓

Poisson regression model. Standard errors, clustered at passer level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Top 5 soccer leagues, 8 seasons: 2011-2019. Half-season: 16-20 games before and after 1 January. Same cultural background is equality of either cultural aspect (language, colonial legacy or nationality). Total team pass count is captured via team *half-season fixed effects. Sequence count is the number of pass sequences, complex seq count is the number of at least 2 pass-long sequences. Total team pass count is captured via team *half-season fixed effects.

Table 7: Pass sequences and complex pass sequences: culture detailed

	pass seq count sequences (1)	complex pass seq count (2)
Same nationality (0/1)	0.0253***	0.0571***
	(0.0045)	(0.0083)
Same colonial legacy (0/1)	0.0202***	0.0413***
	(0.0064)	(0.0109)
Same language only (0/1)	0.0039	0.0339**
	(0.0092)	(0.0141)
Average length of passes (ln)	-0.7007***	-1.724***
	(0.0091)	(0.0140)
Average forwardness Ind (0-1)	0.0839***	-0.5175***
	(0.0102)	(0.0141)
Observations	668,108	644,533
Pseudo R^2	0.74591	0.55971
passer-half_season fixed effects	✓	✓
receiver-half_season fixed effects	✓	✓
passer_position-receiver_position D	✓	✓

Poisson regression model. Standard errors, clustered at passer level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Top 5 soccer leagues, 8 seasons: 2011-2019. Half-season: 16-20 games before and after 1 January. Same cultural background is equality of either cultural aspect (language, colonial legacy or nationality). Total team pass count is captured via team *half-season fixed effects. Sequence count is the number of pass sequences, complex seq count is the number of at least 2 pass-long sequences. Total team pass count is captured via team *half-season fixed effects.

Table 8: Heterogeneity

Heterogeneity source		Freq	Coeff (%)	Diff?
Nationality same as league	Home national	57%	1.70	
	Foreign national	43%	3.40	yes
Player values (euros)	Low (below 3.5m, avg=1m)	27.4%	2.17	
	Medium (1-16m, avg=4.3m)	48.4%	2.60	no
	High (16m+, avg=22m)	22.2%	2.62	no
Age category (ys)	Veteran (29.3+, avg=31.9)	25%	1.99	
	Experienced (23-29.3, avg=26.2)	50%	2.44	no
	Young (below 23ys, avg=21)	25%	3.38	yes
Experience club (days)	Low (below 164, mean: 75)	25%	2.29	
	Medium (165-959, mean 484)	50%	2.70	no
	High (960+, mean: 1850)	50%	2.37	no

Baseline Poisson fixed effect regression model, see Table 3. "Diff?" is statistical difference at 5%. Heterogeneity is defined by the passing player characteristic. Base is first line.

forming the 'majority group', while the 'minority group' consists of players playing in foreign leagues (e.g. Spanish players in Bundesliga or German players in La Liga). To test whether the minority-majority divide is indeed salient, we interact the same culture variable with a binary variable for home or foreign national. Our results support the hypothesis that shared cultural background is more important for minority groups: the homophily premium is about twice as high for players playing in foreign leagues (3.40%) than for players playing in their home leagues (1.70%). This suggests that the homophily bias is stronger when players belong to a cultural minority.

Second, we look at low and high status. A shared cultural background may matter more for low status individuals as long as these may benefit more from trust and information shared by similar others (Ertug et al. (2018)). We use players' valuations to distinguish their different status. We create three groups: low (bottom 25%), medium (middle 50%) and high (top 25%) valued players. We find no significant difference across statuses.

Third, the relevance of same culture may decline over time as players become more familiar with teammates of different cultural background or gain experience in navigating diverse cultural environments. On the other hand, homophilous behavior may become entrenched due to privileged collaboration with similar others. In our setup we devised two metrics to inspect the moderating effect of time. The most obvious measure of time is player age, and we create three age groups: young (bottom 25%, below 23 years), veterans (top 25%, above 29.3 years) and experienced (middle 50%). A clear pattern emerges: the homophily premium is higher for the young (3.38%), lower on

average for the veterans (1.99%) and intermediate for the experienced (2.44%). Hence, age appears to be an important mediator. An alternative measure of time is experience with the current club. This is the moderator that would best capture the idea that working together in a team would tend to eliminate the homophily bias. It is different from age: some young players may have been with the club for several years, while some veterans may have just joined the club. Once again we create three groups, this time by the number of days already spent together at the club at the beginning of a half-season: low experience (bottom 25%), high experience (top 25%) and medium experience (intermediate 50%). We find that experience with the club is irrelevant. Taken together, these findings suggest that the homophily bias may not be reduced by simply spending time together in a team, but may decline as players gain experience in navigating a diverse workplace.

7. Conclusions

We have investigated how homophily based on cultural traits affects collaboration in multinational teams. In doing so, we have collected and exploited a newly assembled exhaustive dataset recording all passes by professional European football players in all teams competing in the top five men leagues over eight sporting seasons, together with full information on players' and teams' characteristics.

The outcome we have chosen as our measure of collaboration is the 'pass rate', defined as the count of passes from a passer to a receiver relative the passer's total passes when both players are fielded together in a half-season. The cultural traits we have focused on are nationality, colonial legacy and language, and we have measured 'culture' through their combination. We have used a dynamic discrete choice model of players' passing behavior as a baseline to separately identify collaboration due to biased cultural preferences ('choice homophily') from collaboration due to opportunities ('induced homophily'). Induced homophily includes domain-specific aspects of collaboration such as the specialization of players with given cultural traits in certain tasks and positions, the correlation between quality and culture or behavioral aspects like patience. Our methodology has also allowed us to exclude mechanisms such as assortative matching of players of similar quality or shared experience.

We have found strong evidence of choice homophily. Relative to the baseline, player pairs of same culture have a 2.50 percent higher pass rate. Same culture is about as likely to lead to more passes as doubling the player pair's valuation, which is a consensus measure of players' skills. As for the different traits, passes between players of same nationality and between players with same colonial legacy but without same nationality are associated with 3.01 and 2.34 percent higher pass rates respectively. Same language with neither same nationality nor same colonial legacy play a negligible role.

We have also found that younger players exhibit stronger choice homophily than older players, with corresponding pass rates of 3.4 and 2.0 percent higher than the

baseline. Belonging to a minority group is also associated with stronger choice homophily: relative to the baseline the pass rate is twice as high for players playing in foreign leagues (3.4%) than for those playing in their own national leagues (1.7%). Sharing a common cultural background is more important for pass sequences than for single passes, with corresponding pass rates of 5.0 and 2.1 percent higher than the baseline. Finally, managers internalize their players' homophilic preferences: players with the same cultural background are selected to play together at 1.4 percent higher frequency than players with different cultural backgrounds.

These findings show that choice homophily based on culture is pervasive even in teams of very high skilled individuals with clear common objectives and aligned incentives, who are involved in interactive tasks that are well defined, readily monitored and not particularly language intensive.

Appendix

A. Football rules

A.1. Key football rules

This subsection describes the key rules in football (soccer). Association football, such as our leagues, is governed by the Laws of the Game[27].

For the purpose of this paper, let us review some key aspects of the game what matters.

In a league, all teams play all other teams twice: in a home and an away game. A team gets 3 points for winning, 1 for drawing and 0 for losing. There is churning season-by season: the worst few (2 or 3) teams every year will be relegated, while a few will be promoted from the lower division to replace them[28].

In a game, there are 2 times eleven players on the pitch. There is freedom in composition, but mostly: 1 goalkeeper, 3-5 defenders (left, center or full- and right-backs), 0-3 forwards, and midfielders. In our data we have very specific positions such as left-back.

The flow of the game is such, that almost two-thirds of the events are passes. In our sample, 62% of events are passes, 77% of which are successful. The rest of the events include shots on the goal, goals, free-kicks, yellow and red cards for disciplinary action, substitutions, tackles and more. There is some variation by teams, some teams pass more than others. Typically better teams pass more.

All decisions on who plays is down to the manager (coach). Each game has a "starting XI" - 11 players who start the game. There are up to 3 substitutions per team/game (this happens typically in the last third of the game). This may happen because of injury or any tactical decision. At all times there will be 11 players on the pitch unless some player gets a red card and is sent out (permanently) - this rarely happens - about once in 5 games.

There is freedom in composition of players, but mostly a team would have: 1 goalkeeper, 3-5 defenders (left, center or full- and right-backs), 0-3 forwards, and a set of defending and attacking midfielders. In our data we have very specific positions such as left-back.

A.2. Teams and transfers

Football teams have squads of about 25-30 players. In Spain, squads are typically smaller: 22-28 players, and in England, larger, with 25-33 players.

Churning is large: 20-40% of team changes season to season. Players leave and arrive, this is called a transfer. Transfers happen twice a year in Europe. The summer

[27]For details see https://en.wikipedia.org/wiki/Laws_of_the_Game_(association_football)

[28]For readers unfamiliar with soccer, we kindly recommend watching https://en.wikipedia.org/wiki/Ted_Lasso.

transfer window is the main opportunity to get new players, or sell existing one. It is between 1 July to 1 September. This is the main window with over 90% of deals in a season. The winter window is shorter, between 1 Jan to 1 Feb, and much smaller. Transfers may include loan deals, when a player spends one or a few half-seasons with another team.

Note that there are games during the window. This generates a complication with respect to measurement - see in Appendix section B.

Finally, players may be "on loan": playing temporarily for a club other than the club which holds their contract. The typical mechanism of a contract is one or two half-seasons, but rarely may be longer.

A.3. Nationality rules in leagues

In some leagues, there is no limit on use of players of any nationality on the pitch, while in others non-EU, especially South American players face some restrictions. Also, some leagues have rules regarding the squad - must have home grown (academy) players - this has very little effect on starting XI. For our five leagues, we have two types of regulations.

Spain, France, Italy do have restrictions on foreign players. Foreign is defined as non-EU. In Spain it is max 3, in France it is max 4 and in Italy, it is max 2 non-EU. For these countries, the non-EU definition varies marginally but include players from 70 countries "Cotonou" agreement + countries offered the same by home country[29]. In Spain, South Americans get citizenship after 5 years, 2 if they can show Spanish ancestry. In Italy, ancestry also allows a fast track to citizenship, which has helped many people from Argentina and Uruguay.

Non-EU restrictions bite for some African/Asian players but mostly South Americans. The result is that in Spain, France and Italy, this regulation will imply that two Brazilians or a Uruguay and Argentina players are less likely to play together than two Europeans.

England and Germany do not have non-EU player restriction. But both have preference for home grown / academy product players, especially Germany. In England, visa restrictions are managed in a way that gives a preference to players who play or have the potential to play for their national team.

We have coded all these rules. Overall, in our estimation dataset, 89% of observations have a passing player who is considered to be unrestricted in the European Union.

Finally note that all personal information for players are dated as of data collection: summer of 2021. This gives rise a tiny bias: as a few players may get a new citizenship overtime, we may only see it for older players who have already got it. This may

[29] https://www.footballmanagerblog.org/2018/04/football-manager-squad-registration-rules.html and on the list of countries, see https://en.wikipedia.org/wiki/Cotonou_Agreement

downward bias our same nationality estimates.

B. Additional information on data and cleaning

In this subsection, we describe important decisions in the process of data wrangling with a focus on how we coded our key variables.

B.1. Defining player nationality, colonial legacy and language

We kept nationalities as defined by the FIFA, ie a nationality is what has a national team. However, as we are interested in country and culture, we formed a team UK: Wales, Scotland, Northern Ireland, and England. Our results are robust to having these countries as colonial links not a same nationality. Similarly Feroer Island and some other geographies are also treated as separate nation.

For country of birth, we sometimes made edits to match current list of countries. Most importantly, for multi-ethnic countries dissolved since (such as Yugoslavia and Soviet Union) born players were given their current nationality if it was part of federation, if not we imputed the largest country (like Russia).

Regarding colony and language definitions, we followed CEPII data[30]. But, in terms of languages and colonial structures, we made some adjustments regarding former countries of Eastern Europe.

- Regarding the former Yugoslavia. We grouped all countries as colonial siblings to encode being in the same country once. We grouped Serbian, Croat, Montenegrin and Bosnian into a same language category.
- Regarding the former Czechoslovakia, Czech Republic and Slovakia are considered both to share the same language and be colonial siblings.
- Regarding the former Soviet Union, we followed CEPII in having Russian as official language in some countries like Kazakhstan. Russian and Belorussian are considered the same language.

Note that similar bit not the same languages like Danish and Norwegian or Russian and Ukrainian were considered as different.

[30]The most frequent official languages (in order of frequency in the estimation dataset) are Spanish, Italian, English, French, German, Arabic, Dutch, Portuguese, and Russian. Other languages in the dataset are: Polish, Serbo.Croat, Bulgarian, Turkish, Czech.Slovak, Swedish, Hungarian, Georgian, Macedonian, Norwegian, Albanian, Ukrainian, Finnish, Danish, Slovene, Greek, Hebrew, Korean, Romanian, Persian, Kimbundu, Icelandic, Hausa, Swahili, Hindi, Afrikaans, Indonesian, Azerbaijani, Comorian, Lithuanian, Tajik, Tigrinya, Malagasy, Kazakh, Latvian, Armenian, Estonian, Haitian.Creole, Kirundi, Filipino, Uzbek, Japanese, Quechua, Chewa, Vietnamese, Amharic, Oromo, Malay, Thai, Mandarin.Chinese, Turkmen, Lao, Dari, Pashto, Kyrgyz, Khmer, Urdu, Hiri.Motu, Tetum, and Bengali

Regarding the decisions on colonial legacy and language, we had to consider pairs with multiple nationalities. For instance, it is possible that two players have both same nationality and same colonial legacy (for example, P1 is Moroccan and French and P2 is French). In such cases, we followed the "topcoding" principle, and they were considered to be of same nationality. This is actually a large set of player pairs, 54% of those who share colonial past will also share a citizenship. As for colonial legacy, the majority of same colonial legacy comes from a link between a ruler (Spain) and a former colony (Argentina). Some links are derived from being colonial siblings, ruled by the same country (Uruguay and Argentina). There are possibilities to have both direct colonial legacy and be a sibling. P1 Is Cote d'Ivoire, P2 is Senegal and France. In an overwhelming case (86%), same colonial history means same language as well. However, this is not the case for all country pairs, such as England and Egypt or Russia and Georgia), and some countries had multiple colonial rules while adopted only one language as widely spoken or official language (such as Cameroon with French). Here, our topcoding implies that these are considered to be in same colony group.

There are several small measurement error issues, all are negligible in impact. First, nationalities may be handed out mid-career. These are typically based on heritage (Italian speaker Argentinians getting Italian citizenship), and it should be a formality rather than a culture change. Second, regarding player values, small measurement errors may come from some low key players having a single year estimate - we replicated it for both half-seasons. Junior team member players promoted to senior team mid-season and would thus have no player value, and we imputed a minimum value here.

B.2. Matching players from two sources and entity resolution

Football players came from two different sources: from the event feed data and from the player information we developed an entity coreference algorithm to match players – find out which records in the two different datasets describe the same player - are coreferent[31].

A baseline solution would be fuzzy matching: use simply the names of the players, with any additional information available, like date of birth, height, nationality and match them based on similarity.

There are several complications for a standard fuzzy matching algorithm for this purpose. First, even for ten thousand players in our sample, it takes a lot of computing power to calculate all possible similarities and find the best ones. Second, simply matching the players by themselves is not precise enough, mostly due to the noise in the data: player features are also not precise and unique[32]. Third, data quality problems

[31]This section is based on the algorithm developed for this project by Endre Borza, see https://github.com/endremborza/encoref

[32]This problem can be demonstrated with an example of teams: in one dataset the names of two clubs are *Athletic* and *Atletico Madrid*, while in the other *Athletic Bilbao* and simply *Atletico*. So the solution must be open to the possibility, that the two entities, *Athletic* and *Atletico* even

mean that some players might have two or more different records in one dataset. Fourth, algorithmic checkups are really important, as re-examining and correcting the possible matches for over ten thousand players is simply not feasible.

Our improved solution relied on introducing "motifs": a combination of player features. The core concept of the improved solution is not to match simply players, but match motifs in a network of players, matches, seasons and teams. This way, already discovered coreferences can be utilized to narrow the search space, and noise in the data can be mitigated by relying on more than one similarity to establish a coreference[33].

The algorithmic matching is not perfect - as players may use different names, especially South American players, and accents may be incorrectly used as well. When the matching score was low, we checked players by hand - about 1% of total names.

B.3. Detailed cleaning steps and decisions

A pass is recorded when it is "Successful" (this means we know which player received the ball), and when player information is not missing. Data quality is rather high. For example in the EP 2014-15 season we had 351,883 passes, of which were 270,118 successful passes (77%). Only 364 has missing IDs, and 62 cases when the passer and receiver is the same.

The estimation dataset is based on the count of passes, and hence contain non-zero counts only. But, there are 52,093 player-pairs*time (7.8%) where only one direction of pass is recorded. As clearly a pass was possible, we added zeroes for these pairs for the opposing direction.

There are several additional steps of data wrangling:

- We dropped observations (N=4000), when a player had a single partner.
- Player age for every season was defined as number of days to 1 September at the actual year. When a player age was missing, we created sample means by teams and seasons and replace missing with that mean.
- When player position was missing, we replaced it with "Central Midfielder".
- When player valuation for a season were missing, we imputed his average valuation overtime. When player valuations were missing, we imputed 100,000 euros. This happens almost entirely for young and new players.
- There are 6 player pairs that moved together to a different club within a time period. We dropped them.

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though are very similar in name.

[33]See more on the algorithm at https://github.com/sscu-budapest/football-data-project/blob/main/reports/coreference_description.md

- As noted earlier, the transfer windows are such that players may move within the window thus playing for more than one team in a half-seasons. In our sample, we observed 954 occasions when players played for two teams within the same half-seasons (374 players who not only moved teams, but also moved leagues). Very rarely (10 player pair – directions), we observe a player pair passing in two different teams in a half-seasons. This is possible because of the transfer window - players may play in Team A for a few games before moving to another team in the same league. We tagged all these 954 events, and kept them only once (in the team they were more active, almost always the second, longer spell).

C. Additional Tables and Results

Table .9: Selection into play: culture detailed

	pass count (1)	Total passes in shared mins (2)	pass count (3)
Same nationality (0/1)	0.0301***	0.0162***	0.0469***
	(0.0048)	(0.0027)	(0.0061)
Same colonial legacy (0/1)	0.0234***	0.0156***	0.0382***
	(0.0066)	(0.0038)	(0.0086)
Same language only (0/1)	0.0066	0.0047	0.0142
	(0.0095)	(0.0050)	(0.0124)
Average length of passes (ln)	-0.7944***		-0.8390***
	(0.0094)		(0.0108)
Average forwardness Ind (0-1)	0.0142		0.1094***
	(0.0099)		(0.0104)
Observations	668,108	668,117	668,108
Pseudo R^2	0.75930	0.86282	0.67156
passer-half_season fixed effects	✓	✓	✓
receiver-half_season fixed effects	✓	✓	✓
passer_position-receiver_position D	✓	✓	✓

Poisson regression model. Standard errors, clustered at passer level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Top 5 soccer leagues, 8 seasons: 2011-2019. Half-season: 16-20 games before and after 1 January. In column 2, the dependent variable is total pass count by player 1 in minutes when both are fielded. Same cultural background is equality of either cultural aspect (language, colonial legacy or nationality). Total team pass count is captured via team *half-season fixed effects.

Table .10: Results on Robustness

	pass count			pass count (ln)	pass count
	(1)	(2)	(3)	(4)	(5)
	Poisson	Poisson	Poisson	OLS	Poisson
Same nationality (0/1)	0.0288***	0.0264***	0.0281***	0.0223***	0.0314***
	(0.0055)	(0.0049)	(0.0047)	(0.0040)	(0.0051)
Same colonial legacy (0/1)	0.0252***	0.0192***	0.0214***	0.0217***	0.0202***
	(0.0076)	(0.0065)	(0.0065)	(0.0052)	(0.0071)
Same language only (0/1)	0.0063	0.0039	0.0059	0.0133*	0.0045
	(0.0111)	(0.0093)	(0.0092)	(0.0072)	(0.0097)
Average length of passes (ln)		-0.7824***	-0.7862***	-0.2898***	-0.8143***
		(0.0094)	(0.0091)	(0.0059)	(0.0114)
Average forwardness Ind (0-1)		0.0112	-0.0027	0.2446***	0.2867***
		(0.0098)	(0.0099)	(0.0043)	(0.0115)
Shared experience (0/1)		0.0104*			
		(0.0056)			
Height difference (cm)		-0.0126***			
		(0.0004)			
Similar valuation (1/0)		-0.0008***			
		(0.0002)			
Both players EU+ (1/0)		0.0065			
		(0.0117)			
Passer total passes when together			1.140***	-0.1309***	
			(0.0048)	(0.0026)	
Observations	668,108	668,108	668,108	669,025	432,125
Pseudo R^2	0.74290	0.76074	0.76039	0.27589	0.71359
passer-half_season fixed effects	✓	✓	✓	✓	✓
receiver-half_season fixed effects	✓	✓	✓	✓	✓
passer_position2-receiver_position2 D	✓	✓	✓	✓	✓

Column 1-3 Poisson, column 4 OLS regression model. Standard errors, clustered at passer level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Top 5 soccer leagues, 8 seasons: 2011-2019. Half-season: 16-20 games before and after 1 January. Same cultural background is equality of either cultural aspect (language, colonial legacy or nationality). Player values are start of the half-season Total team pass count is captured via team *half-season fixed effects. Both players EU+ reflect national regulations to play, see Appendix A.3. Similar valuation and height: both below/above median.

D. Team level evidence: passes and winning

In this appendix, we show the correlation between passing intensity and team performance. For this purpose, we aggregated our estimation dataset to the level of teams and half-seasons. We have N=1,568 observations (16 time periods, 4x20 + 1x18 teams). Team performance is measured as the average number of points won in the time period. (Teams get 0 for a loss, 1 for a draw, 3 for a win.)

We look at how team performance measured by average points is correlated with *ln_apc* defined as log(average pass count per game).

First, we only include league dummies, and show a cross-section correlation for a single half-season (2015-16, H1).

$$Average\_points_{team} = \beta * \ln apc_{team} + \eta_{league} \tag{.1}$$

Then, we estimate a panel fixed effects model adding league-half-seasons and team fixed effects: $team$ and t for half-seasons:

$$Average\_points_{team,t} = \beta * \ln apc_{team,t} + \eta_{team} + \theta_t \tag{.2}$$

Column (1) and (2) has points per game, Column (3) has log(points per game) as dependent variable for easier interpretation. Table .11 presents the results.

Table .11: Team level performance and passes

	points_per_game (1)	points_per_game (2)	ln_points_per_game (3)
Total pass count (ln)	1.142***	0.2471**	0.2095***
	(0.2039)	(0.1168)	(0.0800)
Observations	98	1,568	1,568
Pseudo R^2	0.320	0.725	0.956
leagueseason_half fixed effects	✓	✓	✓
team fixed effects		✓	✓

OLS regression models. Standard errors – robust in Column (1), clustered at the team level in Columns (2) and (3) – are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Team-period level data. German, French, English, Italian, Spanish top soccer leagues. Column 1: First half of 2015/16 season. Columns 2 and 3: 8 seasons 2011-2019. Time period is defined as a half-season, 16-20 games before and after 1 January.

Column (1) reports the cross-section OLS results showing a very strong cross-sectional correlation between points per game and pass frequency. In the panel fixed effect models of Column (2) and 3, we see a smaller but economically significant relationship.

We find evidence that, when teams pass more, they also tend to win more. In Column (2), we regressed points per game (in levels) on log total passes, team and league*half-seasons fixed effects. Conditioning on league specific aggregate trends, in half-seasons when a team passes 10% more than its average pass frequency, it tends to win a 0.025 point (or 2.1%) more than average. Over 38 games, this is 1 point (compared to an average of 50 points per team in a season). This difference is equivalent to one position difference in a typical league's standings.

E. Replication options

As data come from private sources and cannot be made publicly available. Thus, we cannot share the raw data publicly. However, we offer a way to reproduce our results by (i) sharing the estimation dataset with individual identifiers purged the dataset and (ii) sharing all codes, including data cleaning.

Analysis are carried out in R, replication codes will be made available[34].

Furthermore, we will offer access to the data cleaning process with all raw data, with a possibility to run scripts on the full dataset on a secure server. Data wrangling is done in Python, and in R. It will be available on request, and we are currently building a data infrastructure to ease the process.

[34]Codes are stored at the project github page (https://github.com/gbekes/homophily-collaboration), while the data is available from OSF.io (https://osf.io/yc7ux/). These are private repositories at *this* version, access as available on request.

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