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Migrant diversity and team performance in a high-skilled labour market

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Abstract

From a theoretical point of view, the link between workplace diversity and performance in a high-skilled context is ambiguous. Likewise, empirical research at the firm or plant level finds inconclusive and context- specific results. Using a detailed database that covers all the 3,999 matches played by Italian Serie A teams (firms) over a 10-season period, our results reveal a substantial and robust negative effect of fractionalization on performance, whereas no effect is found for polarization. This article also highlights how the negative effect of fractionalization depends on the nature of the tasks to be completed, the wealth of the teams and the level of workers' experience. This work reveals some myopia in hiring practices and suggests that firms should make better decisions in choosing the optimal mix of workers.

1 | INTRODUCTION & MOTIVATION

Challenges such as ageing populations and labour shortages are more relevant than ever before, and high- skilled labour immigration is a potential solution to address them. Consequently, there has been increasing competition for talent worldwide, with national and regional policies being implemented in recent years not only in major Western economies but also in Asian and Latin American countries (Cerna, 2016). For each major economy, attracting high-skilled talent is an important aspect of its national strategy to protect and develop its knowledge base, while, at the same time, economic and health crises and growing political tensions over immigration can be counterproductive. Most recent empirical evidence has found that more diverse high skilled migrants provide a positive economic contribution, especially in richer countries (Ager & Bruckner, 2013; Alesina et al., 2016; Bove & Elia, 2017; Docquier et al., 2020). Nevertheless, when scholars have focused on migrant diversity and its impact on organisational outcomes, the evidence has been ambivalent and contradictory by raising the impact of moderating factors and evaluating the type of empirical strategies adopted in various studies as main contributions to the literature (Dale-Olsen & Finseraas, 2020; Parrotta et al., 2014; Trax et al., 2015).

This paper investigates the impact of migrant diversity on organisational outcomes in a highly competitive industry, with a highly globalised labour market, highly-skilled workers, and an intrinsic production function requiring teams to be cohesive in a very short period. In this organisational context, we argue that cultural diversity harms team performance when the percentage of high skilled migrant workers becomes predominant and workers' tenure declines. According to social identity theory (Tajfel, 1982), more culturally different individuals tend to categorize themselves into specific groups and to assess and judge others as outsiders to protect their social identity. The key assumption is that combining workers from different linguistic and cultural backgrounds within a team could also impose negative externalities - such as transaction costs - as team performance can be affected by a lack of standards in language, expectations, or cultural perspective (Easterly & Levine, 1997; Lazear, 1999).

Within this theoretical context, we contribute to the literature in several ways. Firstly, given that we analyse a labour market that is highly diversified in terms of high skilled migrant workers, we only consider the diversity among foreign-born workers, as suggested by Alesina et al. (2016). This aspect has never been carefully considered by the previous literature on migrant diversity and organisational outcomes. We employ the measures of fractionalization and polarization and study their role in explaining performance (Papyrakis & Mo, 2014). Both measures are distinguishable as they respectively evaluate migrant diversity in quantitative and qualitative terms. While fractionalization considers the degree to which a team is split into distinct migrant groups, polarization reveals the degree of antagonism between the same groups in terms of group identification and the level of alienation toward members of other groups. Despite being used by several macroeconomics studies in different contexts (Alesina & Ferrara, 2005; Esteban & Ray, 2008; Montalvo & Reynal-Querol, 2005), they have never been jointly analysed to assess the impact of team diversity on performance measures. Finally, due to the aforementioned peculiarities of our empirical set-up, we want to better understand the role of heterogeneity and transmission channels within team dynamics. We argue that teams that are more stable in terms of team tenure, are highly reputable in the industry and whose members have more international experience can better mitigate the impact of migrant diversity on their organisational outcomes.

We apply our analysis to the context of the football industry, specifically the Italian Serie A, as it perfectly fits the purposes of our empirical context. Firstly, very accurate and exhaustive information on players' and teams' characteristics and performance is readily available to provide a more detailed analysis than any other industry (Kahn, 2000). Henceforth, we assembled a unique database with detailed information on the athletes and teams for all the matches played in the Italian Serie A – the top Italian football division – from 2009/10 to 2018/19. Then, football clubs operate in a highly competitive and controlled labour market with extreme pressure to win because of the high correlation between their revenue generation and their winning performance (Szymanski & Smith, 1997). Their production function requires quite intense and immediate cohesiveness for a comparatively short period, as a team competes directly against a competitor and potential conflicts within a team are more likely to happen due to the nature of the game (Carmichael et al., 2001; Kahneman, 2011). Moreover, football players are highly-skilled workers, gifted with a high level of specific human capital, and their talent is imperfectly substitutable (Lucifora & Simmons, 2003). Clubs compete to recruit the best talent, regardless of nationality, to maintain and improve their competitiveness. Unsurprisingly, some professional football clubs might select only one or two indigenous players as starters. Finally, football remains a game with a strong cultural identity, as this is still an important aspect for football clubs, their supporters, and national and international governing bodies, which justifies the existence of playing quotas (Gardiner & Welch, 2016). Despite this aspect, as Bryson et al. (2014) found out, foreign players in Italian Serie A benefit from a wage premium as clubs attract more spectators to the stadium when the proportion of migrant players increases. Recently, there has been an increase in studies on the team diversity - performance link using match by match data for football teams. We relate our literature mainly to those studies adopting a similar dataset approach, as it provides a consistent comparison because migrant diversity is directly linked to the team workforce that is employed in each match (Ben-Ner et al., 2017). Looking at organisational subgroups in a football team, Ben-Ner et al. (2017) found both positive and negative performance effects associated with diversity linked to contingencies of task, tenure, and place of origin in the German Bundesliga. Specifically, the effects of diversity on performance are positive for defense and negative for offense. Still using data for the Bundesliga, Brox and Krieger (2019) found evidence of a hump-shaped effect, with a level of diversity maximized for intermediate levels.

Our results show unambiguously that fractionalization - but not polarization - has a negative and robust effect on performance. Reducing the level of diversity by a small amount, *ceteris paribus*, would lead to substantial improvement in the performance of the team. We go on to identify the teams' characteristics that help to mitigate the negative impact of diversity, such as the managers' and players' experience, tenure and stability. With respect to the abovementioned literature, our results do not confirm the non-linear effects of diversity on performance, as found by Brox and Krieger (2019). Our analysis also finds that the impact of diversity is task-specific, with fractionalization in defense explaining the negative effect on performance. Diversity in offense does not have any effect on performance. These findings reveal the importance of high communication costs on the defensive side, a task which requires a high degree of coordination (Lazear, 1999). Such a result is the opposite of the one found by Ben-Ner et al. (2017). Regarding the channels of transmission, we do find that teams with higher levels of diversity commit, *ceteris paribus*, more fouls than more homogenous ones. This is consistent with the interpretation of fractionalization leading to a lower level of coordination and more internal conflict.

The policy recommendations of our work extend well beyond football and can be applied to many other competitive high-skilled labour markets, where firms need to choose the optimal mix for their workforce. Our results indicate that firms should be careful in indiscriminately hiring migrant workers from different countries. This is particularly true for sectors with tasks that require a high degree of communication. Secondly, firms should mix the workforce, placing new foreign workers alongside those who are more experienced.

The paper is organized as follows. Section 2 describes the measure of diversity and the features of the dataset. Section 3 presents the model and the baseline results. In section 4, we provide several robust exercises. The following section highlights the role of heterogeneity and the possible transmission channels. Section 6 concludes.

2 | DATA DESCRIPTION & DIVERSITY MEASURES

2.1 | Description of the Dataset

Our dataset includes ten Serie A seasons – from 2009/10 to 2018/19 – with a total of a) 105,632 player game observations, b) 3,799 games, c) 34 different teams, and d) 1,973 unique players who played at least in one game during our sample period.[1] The analysis was conducted at the match-day level and data were collected from a variety of sources, such as the "Enciclopedia Panini del Calcio Italiano, 1960-2020" (Panini, 2020) and the "Almanacco Illustrato del Calcio (years: 2010-2019)" (Panini, 2019).[2]

Whether we consider either the season or the match level, sporting success is the main target for any professional football. Team league table position, in terms of points attained, is likely to be the most common measure of performance. However, in our context, the analysis is carried out at the match level, which is more suitable for econometric identification. Therefore, our preferred measure of performance is the difference between goals scored and goals conceded by team t in match m and season s, i.e., $\Delta Goals_{t,m,s} = Goals\ Made_{t,m,s} - Goals\ Conceded_{t,m,s}$. Unless otherwise specified, in this article we refer to $\Delta Goals_{t,m,s}$ as $\Delta Goals$. Whenever $\Delta Goals$ is positive, the team wins the game and obtains three points; when $\Delta Goals$ is 0 the team draws and gets one point; when $\Delta Goals < 0$ the

[1]One game (Cagliari-Roma, season 2012–13) is missing, as it was cancelled after the home team's owner urged supporters to ignore the fan ban issued by the local authorities.

[2]The other sources are the Lega Serie A website (legaseriea.it), stadiapostcards.com and the newspaper *La Gazzetta dello Sport*.

team loses and gets 0 points. Given that in each match the $\Delta Goals$ of one team is equal to its negation for the other team, this variable is perfectly symmetrical for the teams playing in the same fixture, ranging from -7 to $+7$. As a robustness check, in section 4, we will also consider the actual points obtained by the team, as another measure of the match performance.

2.2 | Measures of Diversity

In this work we employ two indexes of diversity - fractionalization and polarization - based on the players' country of birth (Alesina & Ferrara, 2005; Ottaviano & Peri, 2006). Although these measures are related, they capture different features of the heterogeneity within a given population. Fractionalization measures the probability that two randomly selected players were born in different countries. It is a variation of the Herfindahl–Hirschman concentration Index (HHI) and is equal to 0 when all individuals are from the same country, and grows as diversity rises.[3] It approaches 1 as the number of individuals increases and each player was born in a different country. Alesina et al. (2016) showed that the fractionalization index - calculated including also native workers - is highly correlated with the share of foreign workers.[4] As such, in the empirical analysis it would be difficult to disentangle the role of diversity among the foreign players from their share. To overcome such a problem, and given the relevance in the Italian context, we rely on an index calculated only among the foreign workers. Formally:

$$Migrant\ Fractionalizaton_{t,m,s} = \sum\nolimits_{i=2}^{N} (sf_{i,t,m,s})(1 - sf_{i,t,m,s})$$

where $s\ f_{i,t,m,s}$ represents the share of foreign players born in country i on the total number of foreign players, with $i \neq 1$, where $i = 1$ represents players from Italy, the native/indigenous group. Again, t stands for team, m for match and s for season. We consider only athletes who played at least 15 minutes in the match, who are more likely to contribute to the outcome of the game (Ben-Ner et al., 2017).[5] To evaluate how the diversity among foreign workers affects performance, we will rely on both *Migrant Fractionalization* and the share of foreign players on the total workforce - i.e., including the natives -, which we label *Foreigner Share*. In other words, we analyse the role of diversity holding the migration rate constant.

We reckon that in the context of Italian Serie A, where the majority of players were not born in Italy, it is more relevant to study the diversity only within the migrant group. The average level of *Migrant Fractionalization* is 0.74, with SD equal to 0.17.[6] Such value is relatively high, and it denotes how football clubs hire players from all around the world. Figure 1 shows the share of Italians and non-Italians over the entire period of 10 seasons. In detail, the number of birthplaces in Serie A is well above an average of 50. The average value for *Foreigner Share* is 0.54, but it conceals a high level of heterogeneity among teams.[7] The share of foreign-born players has progressively increased and in 2018/2019 represented more than 60% of the totality of players. Summing up, the Serie A labour market displays a high volume and diversity of migrant players, which makes a suitable case study to analyse such a research question.

[3] This study often refers to birthplace with the term nationality.

[4] Using the full database, we find a correlation coefficient slightly above 0.9, and highly significant.

[5] Although we recognize that athletes who do not play in the game might also indirectly have an impact of the result, we believe that such contribution has to be considered marginal.

[6] The team that registered the lowest level of diversity was Catania, with an average of 0.21; conversely, Lazio was the team with the highest average equal to 0.83.

[7] The two extremes were International F.C., which played a total of 37 games with only foreign players, and Frosinone and Sassuolo, which played 5 times without a single foreign player.

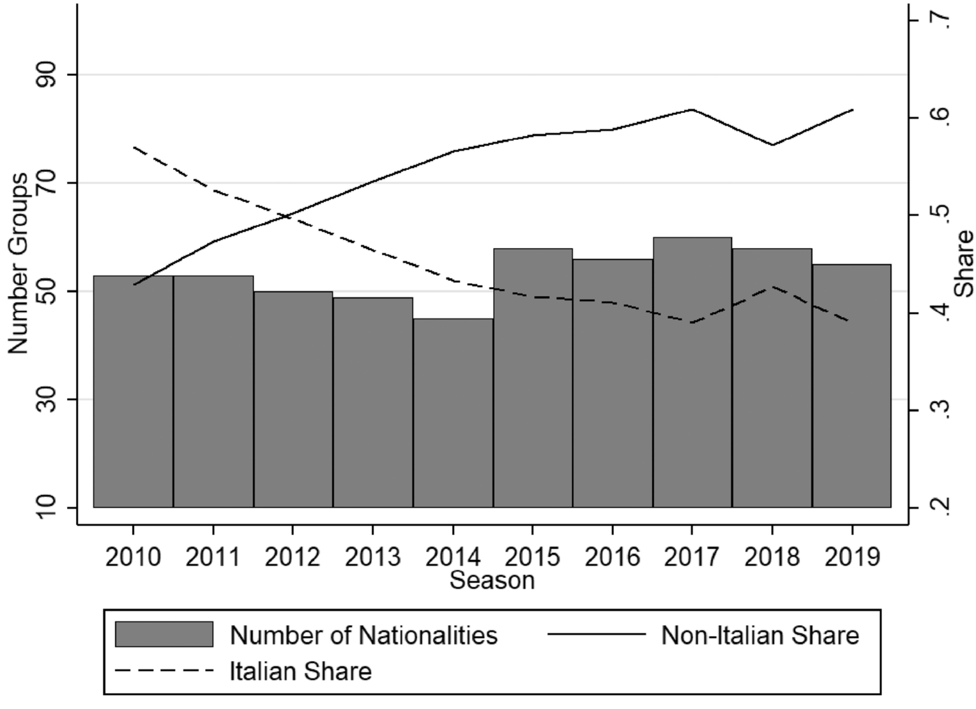

FIGURE 1 Italian vs Non-Italian Shares ***Notes*: This figure represents a) the total number of birthplace nationalities for the 10 seasons under consideration, b) the evolution of Italian and non-Italian shares on the total number of players**

Along with *Migrant Fractionalization*, we also consider the role of another measure of diversity often used in conflict studies, polarization (Reynal-Querol, 2002). As done in the previous section, we calculate such index among the foreign players, in the following way:

$$Migrant\ Polarization_{t,m,s} = 4\sum_{n=2}^{N}(sf_{i,t,m,s})^2(1-sf_{i,t,m,s})$$

We follow the standard procedure and multiply the index by 4 to make it range between 0 and 1. When there are only two groups, both indexes equal the same score. Yet, when we move to three groups, the relationship between these indexes breaks down. Using this alternative index serves as a way of capturing the presence of intra-group tensions (Esteban & Ray, 2008). Economic models of rent-seeking suggest that social costs are higher and social tensions emerge more easily when the population is distributed in two equally-sized groups, therefore when society is highly polarized. Correspondingly, in a football team the coexistence of two equally-sized groups of foreigners, especially if originating from countries characterized by sporting (e.g., Brazil and Argentina) or historical (e.g., Serbia and Croatia) rivalries, may be complex and lead to worse team performance. As can be seen in Table 1, the average value of *Migrant Polarization* is 0.62. Various teams have extreme values, 0 or 1.

By employing both fractionalization and polarization, this work aims at shedding light on the type of migrant diversity that affects performance in firms operating in competitive markets. The fractionalization index allows capturing the role of extreme fragmentation, whereas polarization the importance of groups size. To our knowledge there are no studies we can use to compare our results as the literature at the micro-level has not studied the simultaneous role of fractionalization and polarization on performance.

TABLE 1 Summary Statistics

Variable Name	Definition	Mean	SD
Delta Goals	Difference between goals made and conceded	0	1.715
Foreign Share	Share of players born outside Italy on the total number of players in the game	0.545	0.212
Migrant Fractionalization	Fractionalization index using only the players born outside Italy	0.741	0.170
Migrant Polarization	Polarization index using only the players born outside Italy	0.624	0.183
Age	Average age of the players employed by a team in the game	27.025	1.425
Age Squared	Average age of the players employed by a team in the game squared	732.371	77.476
Number Substitutes	Number of substitutions made by a team in the game	2.928	0.387
Tenure	Average number of seasons spent in their current team by the players employed in the game	1.722	0.868
Serie A	Average number of seasons played in Serie A by players employed by a team in the game	4.005	1.371
International Exp	Proportion of players employed by a team in the game with experience in international competitions	0.838	0.181
International Exp For	Proportion of foreign players employed by a team in the game with experience in international competitions	0.493	0.223
Manager Age	Age of the Manager	49.822	7.331
Manager Experience	Number of matches as a manager	138.281	123.839
Home Court	Home court advantage	0.500	0.500
Attendance/Capacity	Ratio between match-day attendance and stadium capacity	0.585	0.194
Historical Ranking	Overall number of points collected in Serie A by a team over their history before the current season	2130.569	1417.315
Wages	Overall players' payroll of a team (in millions of euro)	45.202	38.462
IVG	Individual match performance indicator	17.719	1.388

3 | EMPIRICAL MODEL, BASELINE

Given that the performance variable, $\Delta Goals$, is symmetrical and can take negative numbers, our starting method of estimation is an OLS fixed effect. The baseline econometric model, which reflects the team production function (Rottenberg, 1956), is the following:

$$\Delta Goals_{t,m,s} = \gamma \; Foreigner\ Share_{t,m,s} + \beta \; Migrant\ Diversity_{t,m,s} + \delta_i X_{t,m,s} + \theta_t + \zeta_s + \varepsilon_{t,m,s} \tag{1}$$

Migrant Diversity could be either *Migrant Fractionalization* or *Migrant Polarization*. $\Delta Goals$ and *Foreigner Share* have been described previously. $\varepsilon_{t,m,s}$ represents the time-varying unobservable error term, which is clustered at the team level (Cameron & Miller, 2015). θ_t and ζ_s are fixed effects at the team and season level. The resulting panel is unbalanced with 34 teams and a maximum of 380 matches for 10 seasons. The number of games is not the same for every team as some are relegated to Serie B at the end of each season. $X_{t,m,s}$ represents a rich set of control variables that also affect the performance of a team. We add these variables gradually, to assess the robustness of β. Their descriptive statistics can be found in Table 1. From column (1) until (3) of Table 2 we consider the role of *Migrant Fractionalization*. In the first column we include only θ_t and ζ_s. The latter captures common shocks across teams in a given season. In column (2), we add the average age of the team and its squared value, to capture potential diminishing marginal returns to age. To take into account heterogeneous dynamics during the match we control for the number of substitutions in a game. We also include a series of variables that capture the level of experience of the players, such as the average tenure in that team. Higher tenure is likely to improve collaboration over time. Furthermore, longer joint tenure improves communication as team members learn each other's styles and reduce misunderstandings (Harrison et al., 2002; Kurtulus, 2011 and Schippers et al., 2003).[8] Continuing, we include the variable *Serie A*, representing the average number of seasons played in Serie A in any team, not only the current one. Serie A is considered among the toughest top leagues and experience might play an important role in determining the outcome of a match. To capture experience deriving from exposure to international competitions we add *International Exp*, which represents the share of players with such exposure. Similarly, *International Exp For* represents such a share only among foreign workers. We also add manager characteristics, such as age and the number of matches managed until then. Many studies have shown that the boss of an organization affects the productivity of their workers (Lazear et al., 2015). In column (3) we add the binary variable *Home*, indicating whether the team was playing in its own stadium. We also include *Attendance/Capacity*, which represents the ratio between match-day attendance and stadium capacity. We control for the historical team ranking and the team payrolls. The former represents the sum of total points obtained by the team in Serie A in all its seasons. The latter is useful to control the available financial resources of the team. Finally, we include the variable *Trend*, which captures the progressive number of matches within a season, along with a binary variable that takes value one if the game is played in the first half of the season and zero in the second part. Fixed effects for the opponents are also included.

Looking at the results in Table 2, the coefficient of *Migrant Fractionalization* is always significantly different from 0 at conventional levels. It is also stable, as it ranges between −0.610, in column (1), to - 0.435, in column (3). To put this into context, taking this last value, an increase of one standard deviation in this variable leads to a decrease in goal differentials by 0.07. That means that a team like Parma in the season 2018/19 would take 14 games to win an extra game if it had the same level of *Migrant Fractionalization* as Napoli. This is a relevant effect, especially in a league where ranking positions are determined within a short number of points. For example, in the 10 seasons under investigation, in six of them the gap to determine the qualification for the Champions League and the teams relegated was 3 points or less. Our findings are similar to other works at the micro-level, such as Parrotta et al. (2014), Kahane et al. (2013) and Lyons (2017). *Foreigner Share* is always positive, but statistically significant only in column (1). Our results are symmetrical to Trax et al. (2015), which found a positive effect of diversity but no effect of the share of migrants.

As mentioned in 2.2, this paper also aims at understating whether having less - but more numerous - migrant groups might have an impact on the teams' performance (Esteban & Ray, 1994). A team with two dominant groups of foreign players might theoretically lead to greater internal conflict. To test this hypothesis, from column (4) until (6) we re-estimate the same models as (1)–(3), using exclusively *Migrant Polarization*. As we can see, the coefficient is never significant. In column (7) we also include *Migrant Fractionalization* in a sort of horse race between the two measures of diversity (Montalvo & Reynal-Querol, 2005). The coefficient for *Migrant Polarization* is not significant and the one for *Migrant Fractionalization* is still significant and negative. Its magnitude is similar to the one found in column (3) of Table 2. The coefficient for *Migrant Polarization* is positive but not significant. In column (8) we further include an interaction term between the two indexes, which is not significant. Overall, we take such results as indicating that, if anything, what is detrimental to team performance is

[8]Harrison et al. (2002) argue that evident aspects of diversity have fewer negative impacts over time because individuals spend more time together to get to know one another better and therefore rely on relatively automatic social categorisation processes, and deep-level diversity becomes more pronounced with more negative effects over time. Schippers et al. (2003) and Kurtulus (2011) find that team tenure enhances the beneficial effects of the diversity - performance relationship.

TABLE 2 The Impact of *Migrant Diversity* on Teams' Performance

	Migrant Fractionalization			Migrant Polarization			Fractionalization + Polarization	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals
Foreigner Share	0.503** [0.244]	0.658 [0.587]	0.512 [0.514]	0.226 [0.225]	0.405 [0.551]	0.341 [0.480]	0.631 [0.528]	0.702 [0.544]
Migrant Fractionalization	−0.610*** [0.209]	−0.591*** [0.169]	−0.435** [0.166]				−0.570** [0.214]	−0.897*** [0.299]
Migrant Polarization				0.043 [0.161]	0.032 [0.153]	0.087 [0.142]	0.240 [0.149]	−0.128 [0.251]
Fract*Polariz								0.917 [0.550]
Age		0.289 [0.501]	0.011 [0.449]		0.327 [0.496]	0.047 [0.446]	0.023 [0.453]	0.054 [0.452]
Age Squared		−0.004 [0.009]	0.001 [0.008]		−0.005 [0.009]	0.000 [0.008]	0.000 [0.008]	−0.000 [0.008]
Number Substitutes		−0.246*** [0.057]	−0.227*** [0.049]		−0.250*** [0.056]	−0.229*** [0.049]	−0.224*** [0.049]	−0.222*** [0.048]
Tenure		0.103** [0.047]	0.072* [0.041]		0.108** [0.048]	0.074* [0.042]	0.072* [0.041]	0.072* [0.042]
Seria A		−0.071** [0.029]	−0.036 [0.030]		−0.080*** [0.029]	−0.042 [0.031]	−0.031 [0.030]	−0.030 [0.030]
International Exp		0.669* [0.334]	0.542* [0.295]		0.604* [0.349]	0.491 [0.309]	0.550* [0.302]	0.521* [0.298]
International Exp For		−0.456 [0.527]	−0.251 [0.453]		−0.482 [0.539]	−0.268 [0.465]	−0.221 [0.453]	−0.216 [0.455]
Manager Age		−0.003 [0.006]	−0.002 [0.004]		−0.003 [0.006]	−0.002 [0.005]	−0.002 [0.004]	−0.002 [0.004]
Manager Experience		0.049 [0.032]	0.032 [0.028]		0.044 [0.033]	0.029 [0.029]	0.033 [0.028]	0.034 [0.028]
Home Court			0.696*** [0.035]			0.696*** [0.036]	0.695*** [0.036]	0.695*** [0.035]
Attendan/Capac			−0.033 [0.178]			−0.030 [0.178]	−0.039 [0.179]	−0.042 [0.179]
Historical Ranking			−0.597** [0.239]			−0.604** [0.238]	−0.629** [0.243]	−0.649** [0.244]
Wages			0.006** [0.003]			0.006** [0.003]	0.006** [0.003]	0.006** [0.003]
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 2 (Continued)

	Migrant Fractionalization			Migrant Polarization			Fractionalization + Polarization	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals
Trend	No	No	Yes	No	No	Yes	Yes	Yes
Half	No	No	Yes	No	No	Yes	Yes	Yes
Opponent FE	No	No	Yes	No	No	Yes	Yes	Yes
Observations	7,598	7,598	7,598	7,598	7,598	7,598	7,598	7,598
Adj. R-sq	0.000	0.006	0.146	−0.001	0.005	0.145	0.146	0.147

Notes: The key explanatory variables are *Migrant Fractionalization* and *Migrant Polarization*, which are indexes of birthplace fractionalization and polarization among non-Italian players. The description of such variables is in the main text. Errors are clustered at the team level.

*p< 0.1, **p< 0.05, ***p< 0.01.

the presence of many groups, whereas having a more polarized workforce is not. In a highly competitive market, like the one of professional football, the greatest cost - in terms of performance - is paid by teams with a workforce too fragmented. These results contribute to the understanding of the type of diversity that affects organizations.

Looking at the other control variables, we note the positive impact on goal difference of the players' average tenure, which indicates that a team with a higher level of familiarity records better performances, consistently with Berman et al. (2002). There is also a positive impact of the players' average international experience, differently from Bykova and Coates (2020). The attendance/capacity ratio has a strong negative impact, suggesting that both home and away teams are negatively affected by a higher level of environmental pressure linked to a higher number of spectators (Boheim et al., 2019), even though this impact is moderated for the home teams by the expected positive coefficient of the home-court advantage.

4 | THREATS TO IDENTIFICATION

In the previous section, we provided evidence that what matters for the firms' performance is the degree of fractionalization, rather than polarization. In light of these results, in this and the following sections, we will mainly focus on the role of fractionalization.[9]

We start showing evidence of the robustness of our results to different variable definitions, econometric techniques and general threats to the identification. We report only the most significant results, while others can be found in the *Supporting Information* document file. With the same concerns in mind, we report exclusively the coefficients for *Migrant Fractionalization* and *Foreigner Share*, instead of the full list of controls. In a recent study, Brox and Krieger (2019) found convincing evidence that the role of diversity on performance might be non-linear. The authors discovered that the relationship is hump-shaped, i.e. it gets its maximum effect for intermediate values of diversity.[10] In column (1) of Table 3, we re-estimated the model in column (3) of Table 2 adding *Migrant Fractionalization* in a quadratic form. The results reveal that this new term is not significantly different from zero, but also that *Migrant Fractionalization* loses significance. A possible explanation of such results is the high level of correlation between *Migrant Fractionalization* and its square, which causes multicollinearity. To take this possibility into account, we centred *Migrant Fractionalization* and recalculated its squared term. We then regress the same model as in (1) with these newly calculated variables. The result shows that *Migrant Fractionalization* is now statistically significant and with a coefficient similar to the one presented in Table 2. The squared term is again not significant. At least for Serie A, the relationship between diversity and performance seems to be linear. Such result is consistent with our theoretical predictions and the majority of the evidence in the literature (Horwitz & Horwitz, 2007; Lazear, 1999). In column (3) we consider an alternative, although complementary, measure of performance. We assign 0 to a loss, 1 to a draw and 2 to a win. We estimate a fixed-effects ordered logit model that confirms our findings.[11] Continuing, one of the main econometric challenges in this work is the potential endogeneity of the variable *Migrant Fractionalization*. The usual suspects are omitted variables bias, measurement error and reverse causality. We think that the first two could be ruled out.[12] The last one might be a concern, if manager might decide to insert more offensive players that are less likely to be national players (Brox & Krieger, 2019). We feel that in our case this is a minor issue. First of all, the share of non-Italian defenders has substantially increased in Serie A, and now it is similar to the one for strikers. Even if substitutes were disproportionately foreigners, the effect on *Migrant*

[9]We have also estimated the models with polarization but the results confirmed that it does not play a role in explaining the teams' performance.
[10]They calculated it including also the native workers.
[11]We employed the command feologit which uses the BUC estimator of Baetschmann et al. (2015). We assume that thresholds are specific to panel units.
[12]Table 2 shows that the results are pretty stable to the gradual inclusion of the control variables. Measurement errors are not a major issue in this context either. It is highly unlikely that data on goals scored and conceded are incorrectly reported. Information on players' birthplace is also recorded with precision.

TABLE 3 Robustness & Threats to Identification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔGoals	**ΔGoals**	**PTS**	**ΔGoals**	**ΔGoals**	**ΔGoals**	**IVG**	**PTS**
	Squared I	**Squared II**	**Ologit**	**45 Min**	**Language**	**Other Diversity**	**Individual**	**Sea**
Foreigner Share	0.549 [0.519]	0.549 [0.519]	0.306 [0.615]	0.438 [0.293]	0.638 [0.483]	-1.451^{**} [0.665]	9.914 [22.344]	27.825 [30.943]
Migrant Fractionalization	−0.104 [0.460]	-0.659^{*} [0.376]	-0.536^{**} [0.242]	-0.282^{*} [0.158]	-0.386^{**} [0.162]	-0.610^{**} [0.304]	-23.091^{*} [12.863]	−16.959 [16.705]
Migrant Fract SQ	−0.375 [0.515]	−0.375 [0.515]						
Age Diversity					-0.162^{***} [0.039]			
Tenure Diversity					−0.001 [0.002]			
Observations	7,598	7,598	15,196	7,598	7,598	96,644	200	200
Adj. R-sq	0.146	0.146		0.147	0.150	0.998	0.172	0.103

Notes: The dependent variable is shown in the header of each column. Column (1) and (2) add a squared term for *Migrant Fractionalization*. In (2) this variable has been centred as well as its square. (3) reports the marginal effects of a fixed effect ordered logit model for the category representing the victory of the team (PTS = 3). The number of observations is double as detailed in Baetschmann et al. (2015). Column (4) only includes players with at least 45 minutes. Column (5) considers a measure of fractionalization based on language, rather than birthplace. In the following column (6), we include measures of diversity based on age and tenure in the team. Column (7) considers data at the player level, with the dependent variable being IVG. In columns (8) and (9) we consider data at the season level. The dependent variables are the total points obtained and the goals difference. All the regressions include the whole set of controls and fixed effects variables. Additionally, column (6) includes player level characteristics. The description of such variables is in the main text. Errors are clustered at the team level.

$^{*}p < 0.1$,

$^{**}p < 0.05$,

$^{***}p < 0.01$.

Fractionalization would be ambiguous.[13] It will increase if the substitute player is from a different country than those already in the match. However, it will diminish if the substitute player is from the same country as the players who are already in the match. In the absence of a reliable instrument, we provide an exercise to rule out the presence of reverse causality.[14] In column (4), we calculate *Migrant Fractionalization* only among the players with at least 45 minutes in the game. By doing this, we are confident that the vast majority of these players started the match, which makes *Migrant Fractionalization* independent of the role of substitutes. Such exercise confirms the negative impact of diversity on performance. In the *Supporting Information* document we consider other measures of diversity based on the language, nationality and formation country of the players. All these exercises reveal significant negative effects on performance. In column (5) we replicate the model in Equation 2, but considering an index of fractionalization based on language rather than birthplace. Our results confirm the ones presented in column (3) of Table 2, which is also in line with the findings of Dale-Olsen and Finseraas (2020). Following on this logic, in (6), we consider types of diversity, based on age and tenure in the team. We calculate them in terms of standard deviations. Results reveal that the coefficient of *Migrant Fractionalization* is barely affected. Teams that are more diverse in terms of age are more penalized, whereas diversity in tenure seems not to have any effect. In column (7), we consider data at the player level. Formally we run the following

$$IVG_{i,t,m,s} = \gamma \; Foreigner\ Share_{t,m,s} + \beta \; Migrant\ Fractionalization_{t,m,s} + \eta_i Z_{i,t,m,s} + \delta_i X_{t,m,s} + \theta_t + \zeta_s + \varepsilon_{i,t,m,s} \tag{2}$$

As a player's performance measure calculated in each match, we used the *IVG* index previously adopted by other scholars (Fumarco & Rossi, 2018).[15] *Migrant Fractionalization*, *Foreigner Share* and the control variables $X_{t,m,s}$ are the same as in Equation 2. $Z_{i,t,m,s}$ is a set of control variables at the individual level. These include the age, age square, tenure seasons in that team, total seasons in Serie A, and whether national and foreign players have international experience. The model includes player fixed effects, and the error terms $\varepsilon_{i,t,m,s}$ are clustered at the individual level. Results show that the coefficient for *Migrant Fractionalization* is negative and statistically significant, but its impact on performance is smaller compared to the one found in column (3) of Table 2. Individual measures of productivity in a team sport are not necessarily revealing of teams' outcomes. Continuing, in columns (8) we employ data at the season level rather than at the match one. As dependent variable, we consider the total amount of points collected. The results reveal a negative impact of *Migrant Fractionalization*, although the coefficient is not statistically significant at conventional levels.

5 | HETEROGENEITY & CHANNELS

The previous analysis provided robust evidence that the level of diversity, as measured by the fractionalization index, hurts performance. The next questions to ask are: what are the teams' characteristics that attenuate or exacerbate the role of diversity on performance? What are the main channels through which fractionalization hampers outcomes? As pointed in the introduction, the literature - especially the one using a similar setting as ours - has provided

[13]Whereas it would change unambiguously if we included the natives in the measurement of the index.

[14]Unfortunately, we do not have any instrument that varies at the match level and is simultaneously correlated with *Migrant Fractionalizaton* and uncorrelated with the error term.

[15]The IVG (index of general evaluation) is not collected at the club level but the player level. More specifically, IVG is calculated for each player in each game. This index represents a concise and objective measurement of a players' performance based on statistics collected through a constant monitoring software-based system of players' and teams' performance (Bacconi & Camillo, 2020). The IVG is expressed on a scale of 30 and it is computed by an algorithm on 1,200 categories of performance data. Among the players' performance features taken into consideration, there are capturing possession, attacking moves (cross, shots, assists) and, for defenders, anticipations, interceptions and tackles. It is important to stress how IVG is a measure of individual performance, which is only partially correlated with goal differentials. Still, our preferred measure is at the team level because it represents a collective effort.

limited answers to such questions. In this section, we fill such a gap, firstly exploring the role of heterogeneity, and then the possible channels.

5.1 | Heterogeneity

Some teams might be better equipped to liaise with higher levels of diversity compared to others. For example, they might have a more stable structure with possibly dedicated programs to help foreign players to integrate into the team, whereas others do not. Although we do not have a measure to capture such team specificity, we suspect that it is monotonically increasing with the wealth of a team. Richer teams are more likely to display a higher level of stability and possibly more resources to be used for these purposes (Goff et al., 2002). To test this intuition, in each season we divide teams into four quartiles based on their wages, and interact them with the level of *Migrant Fractionalization*. Results are reported in column (1) of Table 4. As we can see, the price of a high degree of diversity among foreign players is paid by less equipped teams, whereas richer teams are not affected. This result is also consistent with the ones found by Ingersoll et al. (2017).

Continuing, some authors, such as Forster et al. (2003), noted that the effect of diversity on performance might be task-specific. In particular, the tasks that require a high level of communication and coordination might be more negatively affected by diversity compared to those that rely more on creativity. Translating this to our case, we can separate players into those who play in defense and those in offense. The former task is more mechanical and requires a high degree of communication and coordination, especially in the context of Italian football, that anecdotally dedicates more attention to the defensive side (in all the ten seasons considered the team that conceded the lowest number of goals won the title, whereas only in three seasons the title was won by the team scoring the highest number of goals). On the other hand, the offensive side is less schematic and more creative, therefore relies less on the degree of coordination and communication among individual players. To investigate heterogeneous effects between these two tasks, we create two separate indexes of diversity, one for defense and one for offense. In the defense we include the defenders plus the goalkeeper, whereas in the offense midfielders and forwards.[16] We also calculate the percentage of foreigners per each task, and add them separately in the regression. The results, in column (2), show that the fractionalization among defenders is hurting performance. Diversity among offensive players does not seem to have an impact. We think that the coordination costs among the defensive are higher than for offensive players. In a competitive market with a high degree of pressure, such costs are penalizing. Our results are the opposite of the ones found by Ben-Ner et al. (2017). These authors found a positive and significant effect for defense, but no effects for offense. To study further this aspect, in column (3) and (4) we consider separately *Goals Conceded* and *Goals Made*. Given that the dependent variables are now counts and cannot take negative values, we apply a fixed effect Poisson method. We report its coefficients, i.e. semi-elasticities. As we can see, *Migrant Fractionalization* does not have an impact on goals made, but it harms goals conceded. An increase by 0.1 of *Migrant Fractionalization* is associated with an increase in mean goals conceded by 2.07%. The results reveal, as in (2), that more heterogeneous teams fail in the task requiring high degrees of communication and coordination, i.e., the defense.

Continuing with the exploration of heterogeneity in the impact of *Migrant Fractionalization* on performance, in the following column we interact *Migrant Fractionalization* with some key variables. In column (4) we consider the interaction with *Manager Experience*, that reflects the coaching experience expressed in years. The results show that this variable mitigates the negative effects of diversity. In columns (6) and (7) we interact *Migrant Fractionalization* with *Tenure* and *Serie A*, the average number of seasons in the current team and the average number of seasons in Serie A respectively. In this case, we do find that these variables mitigate the role of diversity. We think that the time spent together by members of a team may improve the quality of their collaboration (Chatman & Flynn, 2001). As such, differences among diverse members may fade away, thus weakening the negative effect of diversity on social

[16] Some midfielders might play a more defensive role, but we do not have such information.

TABLE 4 Heterogeneity in Teams' Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals	ΔGoals
	Wages Pct	Task	Made	Conceded	Manager Experience	Tenure Sea	Serie A
Foreigner Share	0.565 [0.503]		0.332 [0.236]	−0.067 [0.255]	0.472 [0.508]	0.595 [0.493]	0.541 [0.495]
Migrant Fractionalization	0.668 [0.568]		−0.122 [0.101]	0.207** [0.082]	−0.800*** [0.166]	−1.073*** [0.333]	−1.367** [0.502]
Foreigner Share Defense		0.513 [0.660]					
Foreigner Share Offense		−3.061*** [0.632]					
Mig Fra*Wage 1	−1.708** [0.635]						
Mig Fra*Wage 2	−0.922 [0.625]						
Mig Fra*Wage 3	−0.921 [0.791]						
Mig Fra Defense		−0.558*** [0.105]					
Mig Fra Offense		0.232 [0.196]					
Mig Fra*Manag Exp					0.420*** [0.153]		
Mig Fra*Tenure Sea						0.323* [0.159]	
Mig Fra*Serie A							0.215* [0.109]
Wage 1	0.740 [0.664]						
Wage 2	0.611 [0.500]						
Wage 3	0.917* [0.484]						
Manager Experience	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	−0.000 [0.000]	−0.003** [0.001]	0.000 [0.000]	0.000 [0.000]
Tenure Sea	0.089** [0.040]	0.062 [0.045]	0.020 [0.018]	−0.038 [0.024]	0.069 [0.042]	−0.163 [0.110]	0.072* [0.042]
Seria A Sea	−0.048 [0.033]	−0.014 [0.034]	−0.013 [0.017]	0.013 [0.017]	−0.040 [0.030]	−0.035 [0.031]	−0.198** [0.080]

TABLE 4 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ΔGoals	**ΔGoals**	**ΔGoals**	**ΔGoals**	**ΔGoals**	**ΔGoals**	**ΔGoals**
	Wages	**Task**	**Made**	**Conceded**	**Manager**	**Tenure**	**Serie A**
	Pct				**Experience**	**Sea**	
Observations	7,598	7,598	7,598	7,598	7,598	7,598	7,598
Adj. R-sq	0.148	0.159			0.147	0.147	0.147

Notes: The dependent variable is shown in the header of each column. In column (1), in each season we separate teams in four quartiles of total paid wages, and we interact them with *Migrant Fractionalization*. The last quartile is the excluded category. In (2), we create two diversity indexes: one for the defense (goalkeeper plus defenders) and one for the offense (midfielders plus forward). In (3) and (4) we run a fixed-effects Poisson model for goals scored and conceded. From (5) to (7), we interact *Migrant Fractionalization* with three mediating variables. In (5) with the manager's experience, in (6) with the average tenure of players in that team and in (6) with the average number of total seasons played in Serie A, All the regressions include the whole set of control and fixed effects variables. The description of such variables is in the main text. Errors are clustered at the team level.
*p< 0.1, **p< 0.05, ***p< 0.01.

TABLE 5 Potential Channels of Migrant Diversity on Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Fouls Per Game	Red Cards	Yellow Cards	Fouls Per Game	Red Cards	Yellow Cards
Foreign Share	−1.316 [3.575]	6.509 [5.647]	2.748 [25.459]	−0.597 [2.398]	7.650 [4.842]	5.102 [20.303]
Migrant Fractionalization	2.760** [1.157]	−0.213 [2.249]	8.291 [9.899]			
Migrant Polarization				−0.357 [1.334]	3.554 [2.694]	−0.500 [11.295]
Observations	200	200	200	200	200	200
Adj. R-sq	0.573	0.126	0.359	0.460	−0.065	0.207

Notes: The dependent variable is shown in the headers of each column. In column (1) and (4) we consider the impact on fouls per game, in (2) and (5) on red cards and in (3) and (6) on yellow cards. All the regressions include the whole set of control and fixed effects variables. The description of such variables is in the main text. Errors are clustered at the team level.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

preferences towards out-group members. Ben-Ner et al. (2017) found only limited evidence of the interaction of tenure with diversity on performance. Overall, the results in (5) to (7) confirm how the level of experience - at the player, manager and team level - does play an important role in attenuating the negative role of excessive fractionalization.

5.2 | Potential Channels

In the previous sections, we showed how diversity might have a negative toll, especially in more mechanical tasks such as the defense. Here we investigate this idea and identify possible channels through which the lack of coordination and communication might lead to poor results. What is the impact of diversity on other performance determinants? One of the most important of such determinants is team coordination and harmony. Therefore, in Table 5, we explore the impact of *Migrant Fractionalization* on three proxies of poor team coordination: the number of fouls, red and yellow cards. For example, Caruso et al. (2017) used these variables as proxies for conflict. We replicate the analysis in columns (3) and (6) of Table 2, but employing each of the three variables as the dependent one. We report the results for *Migrant Fractionalization* (1–3) and *Migrant Polarization* (4–6). As we can see, only the former is having a significant positive impact on the number of fouls. An increase in one standard deviation of *Migrant Fractionalization* (0.14) leads to an increase in fouls per game by 0.413. This represents an increase of 3%. The effect on red and yellow cards is positive but not statistically significant. We do not find any effect for *Migrant Polarization*.

These results suggest that highly fragmented teams display a poor level of coordination, which, in turn, harms performance. In a context of high players' turnover - such as the Italian Serie A - this could be a serious issue. Finally, the results confirm that it is the *Migrant Fractionalization*, and not *Migrant Polarization*, that is impacting teams' chemistry.

6 | POLICY IMPLICATIONS & CONCLUSION

This paper contributes to the diversity literature by employing detailed employer-employee data for all football matches played by teams in the Italian Serie A over a 10-season period. Differently from previous studies on migrant diversity and organisational outcomes, we only considered the diversity among foreign-born workers (Alesina et al., 2016) - as our analysis focused on a highly diversified labour market - and jointly analysed the measures of fractionalization and polarization (Papyrakis & Mo, 2014). Moreover, we tried to better understand the role of heterogeneity and transmission channels within team dynamics.

In a competitive context with a high level of migration diversity, we find that fractionalization, but not polarization, among foreign players is negatively correlated with team performance. When opening the black box of diversity, this evidence is stronger for smaller teams and among defensive players. Finally, the presence of more experienced players and managers within a team plays a moderating role between diversity and team performance.

Recruiting a higher number of foreign players does not negatively affect team performance *per se*, and in some specifications even has a positive impact. Therefore, the choice to buy a higher number of foreign players is not irrational, as many migrant footballers in Serie A clubs possess both greater talent and popularity (Bryson et al., 2014). However, our results suggest that a higher degree of heterogeneity among foreign players does hurt team performance. Therefore, Italian clubs should be aware that an excessive mix of foreign players, bringing different languages, cultures, football education, and playing styles, can become an additional counterproductive factor on team performance. This result is more relevant when we focus our attention on smaller teams, which are less stable – due to the high level of staff turnover – and less resourceful than bigger clubs. This evidence might suggest that small clubs are still struggling to adopt adequate measures to integrate foreign players in comparison with the bigger clubs. Finally, we find that experience is a key factor to mitigate the effect of a higher degree of heterogeneity among foreign players. Our evidence suggests that teams with more experienced players and managers might be more effective in addressing and leading a multitude of foreign players than teams whose experience is still limited.

In light of these results, we recommend that the implementation of three specific recruitment policies and strategies might mitigate the diversity issues by better integrating different groups of foreign players: a) to prioritize the acquisition of foreign players who have already accumulated a certain degree of experience in the domestic league; 2) to take into account that the integration of foreign players is more relevant in defense than in any other playing position; 3) to consider that a team led by experienced and charismatic players can generate a more inclusive environment. Finally, these results may be valid not only for football, but also for a variety of competitive high-skilled labour markets with a high degree of pressure. Further research should try to replicate our analysis in other labour markets with similar characteristics to verify whether our results apply to such contexts.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Panini Digital. Restrictions apply to the availability of these data, which were used under license for this study.

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