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Birthplace Diversity and Team Performance

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Abstract

We present a simple model to illustrate how birthplace diversity may affect team performance. The model assumes that birthplace diversity increases the stock of available knowledge due to skill complementarities and decreases efficiency due to communication barriers. The consequence of these two opposing effects is a hump-shaped relationship between birthplace diversity and team performance. To verify this prediction, we exploit self-collected data on the first division of German male soccer. Our data set covers 7,028 matches and includes information about 3,266 players coming from 98 countries. We propose two different instrumental variable approaches to identify the effect of birthplace diversity on team performance. Our findings suggest that an intermediate level of birthplace diversity maximizes team performance.

Keywords: *Birthplace diversity, firm performance, globalization, high-skilled migration, international migration, productivity, soccer, team composition, team performance*

JEL No.: F23, F66, J01, J24, M14, M54

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1 Introduction

The increasing importance of team-based production (see Deming, 2017, Jones, 2009, Wuchty et al., 2007) and the increasing number of multinational working groups (see Alesina et al., 2016) make the question of how birthplace diversity[1] influences team performance to an issue of high economic relevance. Addressing this open question is difficult for three reasons. First, birthplace diversity has positive and negative effects: while complementary skills and experiences improve team performance, communication barriers reduce working efficiency and thus productivity (Freeman and Huang, 2015). Second, the data requirements for an empirical study are exceptionally high (Kahane et al., 2013). Third, various endogeneity problems complicate an identification of the causal effect.

This paper addresses these three issues and offers new insights into the relationship between birthplace diversity and team performance. We start with a simple model to illustrate that birthplace diversity may have a hump-shaped effect on the performance of a working group. We then present a comprehensive data set including information on German soccer teams and explain why our data is suited for testing the key predictions of our model. Finally, we report results from two-stage least squares regressions that confirm the existence of a hump-shaped relationship between birthplace diversity and team performance.

In our model, the output of a working group depends on two factors: the available knowledge and the efficiency with which the members of a team collaborate with each other. We argue that birthplace diversity influences both of these factors. On the one hand, individuals born in different countries and educated under different systems have different ideas and productive skills. The stock of available knowledge thus increases if the members of a team originate from different countries (Alesina et al., 2016). On the other hand, when people with different origins collaborate, they often face cultural and linguistic barriers. Birthplace diversity thus reduces the efficiency of the collaboration (Lazear, 1999). Our model implies that the consequence of the opposing aspects is a hump-shaped effect of birthplace diversity on team performance.[2]

Finding suitable data is a key obstacle when investigating the relationship between birthplace diversity and team performance. We address this issue with data from the highest division of male soccer in Germany (*Bundesliga*). We use soccer data for three reasons: first, we observe who collaborates with each other; second, we can easily and precisely measure the performance of a soccer team, and finally, much information on soccer players is publicly available.

Our data set includes information on 7,028 Bundesliga matches. We know the final result of each match and have a full list of the fielded players. To create this list, we

[1]Following Alesina et al. (2016), we define "birthplace diversity" as the probability that two randomly selected members of a group have different countries of birth.

[2]It is important to note that the optimal level of birthplace diversity is task-specific. Our model implies that the optimal level of birthplace diversity decreases if the importance of verbal communication and personal interaction increases. We show estimation results that are consistent with this prediction.

digitized match reports published by the German sports magazine *Kicker*. The total number of players that were fielded in at least one Bundesliga match is 3,266. For each player, we identified the country of origin in order to produce team-level measures of birthplace diversity. We also collected other information, especially two variables that indicate the quality of the players.

Previous studies using data from sports industry to examine the effect of birthplace diversity and team performance apply fixed effect models (see Haas and Nüesch, 2012, Kahane et al., 2013). This conventional approach is inappropriate in our case since it creates estimates that underestimate the true optimal level of birthplace diversity. The major reason is that birthplace diversity increases during a match if a team performs badly. We show that team managers replace defensive players with offensive players if their team is behind (see also Garicano and Palacios-Huerta, 2014). These substitutions often have no effect on the final score of a match, but they often increase the birthplace diversity of the team because the share of foreigners in German clubs is usually larger among offensive player than among defensive players.

We address endogeneity issues with two instrumental variable approaches. Our first approach uses starting line-ups that were predicted by the soccer magazine *Kicker* and exploits the birthplace diversity in these predicted line-ups as the instrument for the birthplace diversity of the fielded players. In the second approach, we use unexpected changes in the birthplace diversity of the starting players to create plausibly exogenous variation.[3] As a robustness check, we only exploit those unexpected changes that are explainable with injuries.

The results of our instrumental variable regressions suggest that the relationship of birthplace diversity and team performance is hump-shaped, and thus confirm the key prediction of our stylized model. The predicted optimal level of birthplace diversity is around 0.6. Put differently, we observe that team performance is maximized when the probability that two randomly selected members of a team have different countries of birth is 60 percent. We also find that a change in birthplace diversity by 10 percentage points in either direction of the optimal level lowers team performance by 3 percent of the sample mean.

The literature includes only a few empirical studies that investigate how birthplace diversity affects team performance.[4] None of them tests whether this effect is hump-shaped.[5] Lyons (2017) designs an experiment in which programmers from Bangladesh, Pakistan, and India are randomly assigned to teams. She observes that multinational teams are less productive than homogeneous teams. Freeman and Huang (2015) show

[3]To identify "unexpected changes", we compare the actual starting line-up with the expected starting line-up published by *Kicker* at the day before a match day begins.

[4]For macroeconomic studies on the relationship between birthplace diversity and economic growth, see Ager and Brueckner (2013), Alesina et al. (2016), Bove and Elia (2017), Docquier et al. (2018), and Ottaviano and Peri (2005). For studies on the effect of birthplace diversity on firm performance, see Parrotta et al. (2014) and Trax et al. (2015). For studies on the effect of ethnic diversity on team performance, see Hjort (2014) and Marx et al. (2018).

[5]Ashraf and Galor (2013) find country-level evidence for a hump-shaped relationship between genetic diversity and economic development.

that nationally diverse research teams publish more often in high impact journals than nationally homogeneous research teams. Kahane et al. (2013) use data from the NHL (National Hockey League) and report that team performance positively correlates with the share of foreign team members, while birthplace diversity is negatively correlated with team performance.[6]

Our paper also relates to the literature that uses data from the professional sports industry to answer economic questions. Kleven et al. (2013) use information from the European soccer market to estimate the effect of top tax rates on migration. Parsons et al. (2011), Price and Wolfers (2010), and Price et al. (2013) investigate same-race preferences, using sports data from the United States. Arcidiacono et al. (2017), Gould and Winter (2009), and Guryan et al. (2009) exploit sports data to analyze the role of peer effects. Krumer and Lechner (2018) and Lichter et al. (2017) use data from the Bundesliga to examine the role of scheduling in tournaments and to estimate the effects of air pollution on productivity. Apesteguia and Palacios-Huerta (2010) and Garicano et al. (2005) exploit soccer data to study the consequences of social and psychological pressure.

We proceed as follows. Section 2 presents our model. Section 3 informs about the Bundesliga and our data. Section 4 describes our identification strategies. Section 5 presents our estimation results. Section 6 concludes.

2 Conceptual framework

In this section, we develop a simple theoretical model that illustrates how birthplace diversity may affect team performance. This model has two purposes: first, it gives an intuition about the mechanisms through which birthplace diversity influences team performance, and second, the key predictions of the model serve as our guide in the empirical analysis presented in Sections 4 and 5.

We consider a team that consists of n workers originating from m countries. Each worker i has two traits: an origin-specific trait ($q_i \in [0,1]$) and a personality trait ($p_i \in [0,1]$) that does not depend on the country of origin. $\mathbf{A} = \{a_{ij}\}_{i,j=1,\dots,n}$ denotes a similarity matrix in which $a_{ij} = 1 - |q_i - q_j| \in [0,1]$ reflects the extent to which the origin-specific traits of workers i and j resemble each other. Following Bossert et al. (2011), we define that the birthplace diversity of the team ($\delta \in [0,1]$) only depends on the similarity matrix $\mathbf{A}$:

$$\delta = \delta(\mathbf{A}) = 0 \quad \Leftrightarrow \quad a_{ij} = 1 \quad \text{for all } i,j = 1,\dots,n \tag{1}$$

$$\delta = \delta(\mathbf{A}) = 1 \quad \Leftrightarrow \quad a_{ij} = 0 \quad \text{for all } i,j = 1,\dots,n \text{ and } i \neq j \tag{2}$$

[6] In the management literature, some empirical studies use data from the Bundesliga to investigate the relationship between birthplace diversity and team performance (see Haas and Nüesch (2012), Nüesch (2009) and Brandes et al. (2009)). All of these studies use a fixed effect approach and thus do not take into account the potential endogeneity of birthplace diversity over the course of a match/season.

$$\delta_{a_{i,j}} = \frac{\partial\,\delta\big(\mathbf{A}\big)}{\partial\,a_{i,j}} < 0 \quad \text{for all } i,j = 1,\,\ldots,\,n \text{ with } a_{ij} \in (0,1). \tag{3}$$

The performance of teams depends on two factors. The first factor is the available knowledge:

$$H = H\big(\delta,\,\rho,\,\Sigma_Q,\,\Sigma_P\big) \geq 1 \quad \text{with} \quad \Sigma_Q = \sum_{i=1}^{n} q_i \quad \text{and} \quad \Sigma_P = \sum_{i=1}^{n} p_i \tag{4}$$

where Σ_P and Σ_Q capture the abilities of the team members and $\rho \in [0,1]$ is the diversity of the personality traits. We assume that birthplace diversity increases the available knowledge because workers born in different countries grow up under different cultural and educational systems and are thus likely to have distinct productive skills (Alesina and La Ferrara, 2005, Alesina et al., 2016, Ashraf and Galor, 2013):[7]

$$H_\delta = \frac{\partial\,H}{\partial\,\delta} > 0 \quad \text{with} \quad \lim_{\delta\to 0} H_\delta = \infty \quad \text{and} \quad \lim_{\delta\to 1} H_\delta = 0 \quad \text{and} \quad H_{\delta\delta} \leq 0. \tag{5}$$

The other factor of team performance is the efficiency with which the team members collaborate with each other:

$$E = E\big(\delta,\,\rho\big) \in (0,1] \quad \text{with} \quad E(0,0) = 1. \tag{6}$$

The efficiency of the collaboration decreases in birthplace diversity since workers from different countries are likely to face cultural and linguistic barriers (Freeman and Huang, 2015, Lazear, 1999):

$$E_\delta = \frac{\partial\,E}{\partial\,\delta} < 0 \quad \text{with} \quad \lim_{\delta\to 0} E_\delta > -\infty \quad \text{and} \quad E_{\delta\delta} \leq 0. \tag{7}$$

Assuming a Cobb-Douglas production function, the output of a team is then given by:

$$Y = E\big(\delta,\,\rho\big)^{\alpha} \cdot H\big(\delta,\,\rho,\,\Sigma_Q,\,\Sigma_P\big)^{1-\alpha} \quad \text{with} \quad \alpha \in (0,1), \tag{8}$$

and the first-order condition with respect to δ can be written as:

$$0 = \alpha \cdot E_\delta \cdot \left(\frac{H\big(\delta,\rho,\Sigma_Q,\Sigma_P\big)}{E\big(\delta,\rho\big)}\right)^{1-\alpha} + (1-\alpha) \cdot H_\delta \cdot \left(\frac{E\big(\delta,\rho\big)}{H\big(\delta,\rho,\Sigma_Q,\Sigma_P\big)}\right)^{\alpha} \tag{9}$$

From (9), we obtain the following results:

Proposition 1. *Conditional on all other determinants of team performance, it holds that:*

(a) Team output Y is a concave function of birthplace diversity δ.

[7] In line with several related studies, we implicitly assume that different skills complement each other.

(b) *Team output Y is maximized at an intermediate level of birthplace diversity $\delta^* \in (0,1)$.*

(c) *The more important efficient collaboration is for team output, the lower is the optimal level of birthplace diversity:*

$$\frac{\partial \delta^*}{\partial \alpha} < 0 \quad \textit{with} \quad \lim_{\alpha \to 0} \delta^* = 1 \quad \textit{and} \quad \lim_{\alpha \to 1} \delta^* = 0.$$

3 Data and institutional framework

Finding data that is suited for an examination of the relationship between birthplace diversity and team performance is difficult because we require: (i) an environment in which individuals from different countries collaborate with each other, (ii) information about the composition of working groups, (iii) data on workers' country of birth, skills and experiences, and (iv) a measure of the output of the collective effort (Kahane et al., 2013). This section shows that we meet these requirements when using data from the *Bundesliga*.[8]

3.1 Institutional background

The Bundesliga—the highest division of German male soccer—consists of 18 clubs and its matches are organized as a double round-robin system. Each club plays 34 matches per season, 17 of them at home. Bundesliga matches are played in prespecified match days and usually take place on weekends.[9] Seasons are divided into two rounds (August – December, January – May) and a break of four/five weeks without matches is made between the first and the second round. In both rounds, a club plays against all other clubs. If a club has the home field advantage in the first round, the opponent has the home field advantage in the second round.

A soccer match lasts 90 minutes and consists of two halves. Prior to the match, the team manager nominates 11 starting players (1 goal keeper, 10 field players) and 7 substitutes. During a match, the team manager can substitute up to 3 players. At the end of a match, the winner obtains 3 ranking points, while the loser obtains 0. In case of a draw, both clubs obtain 1 ranking point.[10]

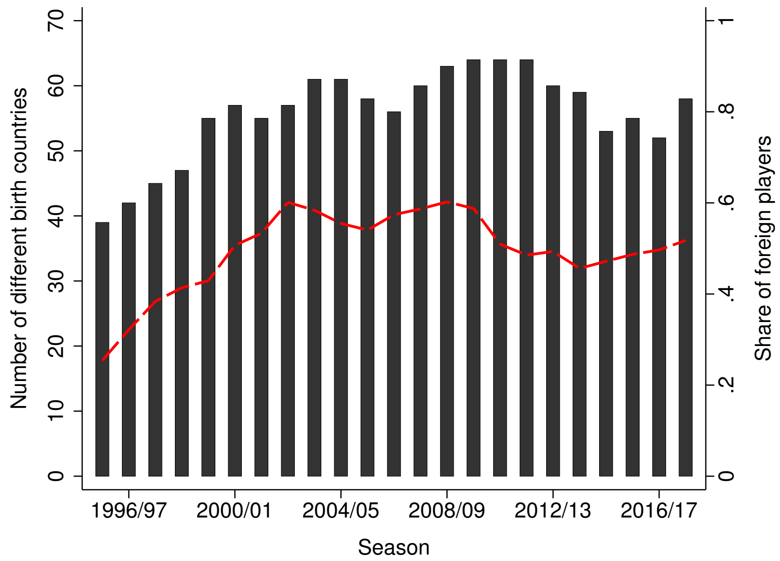
The starting players and the substitutes are selected out of the squad. The squad includes all soccer players hired by the club and is compiled by the club managers who

[8]The literature includes numerous studies that exploit data from sports industry to address economic questions (for surveys, see Fizel (2017) and Leeds et al. (2018)). In particular, Kahane et al. (2013) exploit data from the National Hockey League (NHL) to estimate the effect of birthplace diversity on team performance. We prefer the Bundesliga over the NHL for two main reasons: first, the share and diversity of foreign players is much greater, and second, the better data availability allows for more sophisticated identification strategies.

[9]For organizational reasons, some match days have to take place during midweek days (Tuesday and Wednesday). For details, see Krumer and Lechner (2018).

[10]At the end of a season, the total number of ranking points determines the position in the final table. If two clubs have the same number of points, the difference between the number goals scored and goals allowed serves as the decision criterion.

Figure 1 Trends in birthplace diversity — Bundesliga, 1995/96 – 2017/18.



Notes: The dashed red line illustrates how the share of foreign *Bundesliga* players developed over time. All figures are weighted by the number of matches. The bar chart shows how the number of birth countries changed over time

can change the squad twice a year. The first transfer period is in July and August, the second is in January. There are no regulations about the size of the squad. A salary cap does not exist and budgets differ across clubs. The club budget depends on ticket sales, TV revenues, sponsorship contracts, transfer revenues, and monetary rewards for participation in European club tournaments.

The rule governing the fielding of foreign players has only changed twice since the introduction of the Bundesliga in 1963. The initial regulatory scheme lasted until the middle of the 1995/96 season and allowed the fielding of three foreigners. In December 1995, the European Court of Justice declared the initial form of the *three-players rule* illegal on the grounds that it is not compatible with the treaties of the European Union (Dobson and Goddard, 2011).[11] Afterwards, a *three-players rule* only applied to non-European players.[12] As of the 2004/05 season, also this restriction was abolished.

The dashed line in Figure 1 illustrates how the share of foreign Bundesliga players changed over time (right scale). In the 1995/96 season, only about one quarter of the Bundesliga players was not German-born. Caused by the relaxation of the *three-players rule*, the share of foreigners began to increase in the 1996/97 season and peaked at 60 percent in the 2002/03 season. Since the 2010/11 season, about half of the Bundesliga players are German-born.

[11] This landmark decision is known as *Bosman ruling* and is named after the Belgian Jean-Marc Bosman who sued his club, RFC Liège, because of contractual disputes. For details, see Dobson and Goddard (2011), Kleven et al. (2013), and Simmons (1997).

[12] This rule had, however, rather little practical relevance since most of the non-Europeans had a dual citizenship of their country of birth and an European country.

Figure 1 also includes a bar chart suggesting that the Bundesliga players come from various countries (left scale). The length of a bar corresponds to the number of birth countries. Between the 1995/96 season and the 2003/04 season, the number of birth countries increased from 39 to 61. Since then, the number of birth countries oscillates between 52 and 64.

3.2 Data

We created a new database including information on all Bundesliga matches from the 1995/96 season up to the 2017/18 season.[13] In total, we have information on 7,038 matches and 3,266 soccer players that originate from 98 countries (for a list, see Table C.1).

For each match, we know the date, the participating clubs, the final result, and the venue. We also observe the starting line-ups, have precise information on substitutions, know the ranking position of a club prior to a specific match, identify whether a club participated in a match of a European club tournament or the national cup in the week just before or immediately after a Bundesliga match, and know the name of the team manager in charge. To obtain these information, we use the homepage of the leading soccer magazine magazine *Kicker* (`www.kicker.de`).

In accordance with the related literature, we use two measures of performance. The first is the number of ranking points that the club obtains at the end of a match. Our second measure is the difference between goals scored and goals allowed.

We use multiple sources[14] to identify the country of birth of all $3,266$ players who participated in at least one Bundesliga match since July 1995. To measure birthplace diversity, we calculate *Indices of Fractionalization*:

$$\text{BDiv} = 1 - \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} \tag{10}$$

where n is the number of team members and a_{ij} reflects the similarity of the origin-specific traits of players i and j. Creating (10) requires two steps. In the first step, we define which players of a club constitute the "team". Our baseline approach is to incorporate all players that played for at least 1 minute in a particular match.[15] The second step specifies the similarity matrix $\mathbf{A} = \{a_{ij}\}_{i,j=1,\ldots,n}$. Following Alesina et al. (2016), we set a_{ij} equal to one (zero) if player i and player j have (do not have) the same country of birth. *BDiv* thus indicates the probability that two randomly drawn team members were born in different countries.

[13] We began the data collection with the 1995/96 season for three reasons: (i) prior to this seasons, it was prohibited to field more than three foreigners, (ii) as of this season, the winner of a match obtains 3 ranking points, and (iii) data quality.

[14] Our primary sources of information are the *Kicker* homepage (`www.kicker.de`) and the databases *Transfermarkt* (`www.transfermarkt.com`) and *World Football* (`www.worldfootball.net`).

[15] Section 5.3.3 shows that our estimation results remain virtually unchanged when using players that played for at least 30 minutes.

For each player, we know the date of birth, the date at which he was hired, and the number of matches that he has played prior to a particular Bundesliga match in (i) the Bundesliga, (ii) the highest soccer divisions in France, England, Italy, and Spain, (iii) an European club tournament, and (iv) European and world championships.[16] These information come from the online databases *Transfermarkt* (`www.transfermarkt.com`) and *World Football* (`www.worldfootball.net`). Furthermore, our dataset includes two expert-based measures of players' quality. The first is the market value as reported by *Transfermarkt*. Our second measure of quality comes from the video game series *FIFA* which is released annually by the video game company *Electronic Arts*. In this popular video game, each player has a playing strength ranging from 0 to 100. We use a PHP script to download these ratings from the *FIFA* online database (`www.fifaindex.com`). Our two measures of players' quality have the shortcoming that they are only available for the 13 latest seasons (2005/06 – 2017/18).

4 Empirical framework

4.1 Fixed effect model

The key predictions of the model presented in Section 2 suggest that the relationship between birthplace diversity and team performance can be well described with the model:

$$\mathrm{Y}_i \;=\; \beta_1 \cdot \mathrm{BDiv}_i \;+\; \beta_2 \cdot \mathrm{BDiv}_i^2 \;+\; \gamma \cdot \mathbf{X}_i \;+\; \varepsilon_i \tag{11}$$

where i is the team, *BDiv* the level of birthplace diversity, and Y the measure of performance. $\boldsymbol{X}$ includes other factors of team performance and ε denotes the error term. The optimal level of birthplace diversity is then:

$$\mathrm{BDiv}^* \;=\; -\,\frac{\beta_1}{2 \cdot \beta_2} \quad \text{with} \quad \beta_1 \in [0,\, -2 \cdot \beta_2] \quad \text{and} \quad \beta_2 \,<\, 0. \tag{12}$$

Estimating the parameters β_1 and β_2 is challenging for several reasons. A major difficulty is to specify the vector $\boldsymbol{X}$ such that the point estimates of β_1 and β_2 do not suffer from an omitted-variable bias. Our baseline analysis addresses this issue in the following way. First, we use a rich set of fixed effects to capture all factors that are specific to a club in a round of a particular season if a particular team manager is in charge. These factors include: the abilities of the manager and his staff members, the composition of the squad, the budget and prestige of a club, the quality of the training center and youth section, and the fan base. Furthermore, we add variables to $\boldsymbol{X}$ that reflect the experience and the skill level of the team members. We also control for the home field advantage and take the opponent into account.

Our basic regression model is:

[16]We choose the leagues of France, England, Italy, and Spain since the level of play in these league is similar to the level of play in Germany.

$$\mathrm{Y}_{isrmd} = \beta_1 \cdot \mathrm{BDiv}_{isrmd} + \beta_2 \cdot \mathrm{BDiv}^2_{isrmd} + \gamma \cdot \mathbf{X}_{isrmd} + \xi_{isrm} + \theta_d + \varepsilon_{isrmd} \quad (13)$$

where i is the club, s the season, m the manager, and d the match day. $r \in \{1, 2\}$ indicates whether a match belongs to the first/second round of a season. $\boldsymbol{X}$ includes several team, manager, and opponent characteristics (for a list, see Table C.2). ξ is a club-by-season-by-round-by-manager fixed effect and θ a match day fixed effect.[17]

The estimates of β_1, β_2, and $BDiv^*$ that we obtain when estimating (13) might be biased for three reasons. First, the fixed effects and control variables do not suffice to capture all confounding factors. Second, the measure of birthplace diversity may suffer from measurement error and thus creates an attenuation bias. Third, reverse causality may exist because the composition of a team changes over time and these changes may depend on the performance of a team.[18]

4.2 Two-stage least squares model

We believe that reverse causality is the most serious endogeneity problem[19] and that it causes a downward bias in the estimates of the optimal level of birthplace diversity ($BDiv^*$). The reason is that a team manager replaces defensive players with offensive players during a match when his team is behind (Garicano and Palacios-Huerta, 2014). These performance-related substitutions often do not have an effect on the result of a match, but often increase birthplace diversity since German soccer clubs usually hire much more foreign offensive players than foreign defensive players (for a more detailed description, see Appendix A).

4.2.1 Diversity in the starting line-up predicted by *Kicker*

We allay endogeneity concerns with two instrumental variables approaches. The first approach exploits information from the prestigious soccer magazine *Kicker*. For each Bundesliga match, *Kicker* publishes an expected starting line-up at the day before the first match of a match day begins. We digitized all 7,956 expected starting line-ups published between July 2005 and June 2018[20] and identified the country of birth of all listed players. We use these information to estimate the first-stage equations:

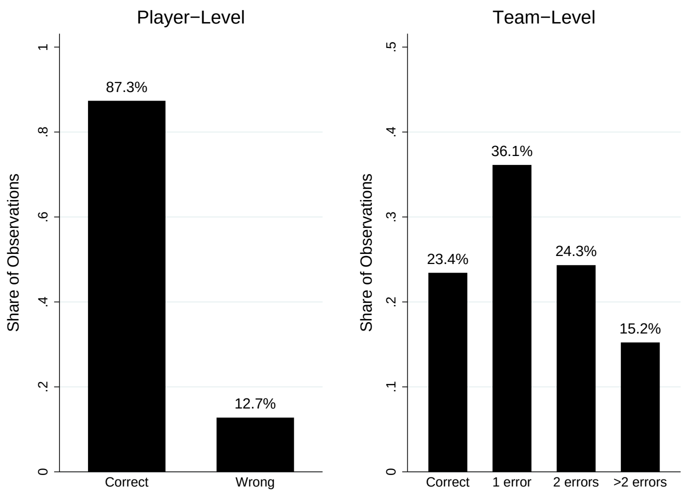
[17] For example, in the second round of the 2008/09 season, Jürgen Klinsmann was the responsible team manager of Bayern Munich in the first twelve matches, while Jupp Heynckes was the team manager in charge in the last five matches. The fixed effect ξ controls for the mean performance within each of these periods and absorbs all club-, manager-, round-, and season-specific factors that do not change over the course of each of these periods.

[18] For a detailed discussion of why and how the composition of a working group changes over time, see Arrow et al. (2000).

[19] The large number of fixed effects and the rich set of control variables, which especially includes two measure of quality, make us confident that "omitted factors" are much less likely to be a source of significant bias than "reverse causality". The fixed effect and instrumental variable estimates that we report in Section 5 are consistent with this presumption.

[20] We cannot expand the sample because of limited data availability and low data quality.

Figure 2 Accuracy of the predicted starting line-up.



Notes: The left graph shows how likely it is that a player who is part of the starting line-up predicted by *Kicker* also belongs to actual starting line-up. The right graph shows how likely it is that there are no (one, two, or more than two) discrepancies between the starting line-up predicted by *Kicker* and the actual starting line-up.

$$\mathrm{BDiv}_{isrmd} = \rho_1 \cdot \mathrm{K}_{isrmd} + \rho_2 \cdot \mathrm{K}^2_{isrmd} + \alpha \cdot \mathbf{X}_{isrmd} + \xi_{isrm} + \theta_d + \eta_{isrmd} \quad (14)$$

$$\mathrm{BDiv}^2_{isrmd} = \delta_1 \cdot \mathrm{K}_{isrmd} + \delta_2 \cdot \mathrm{K}^2_{isrmd} + \lambda \cdot \mathbf{X}_{isrmd} + \xi_{isrm} + \theta_d + \mu_{isrmd} \quad (15)$$

where K is the birthplace diversity in the starting line-up predicted by *Kicker*.

Figure 2 shows the relationship between the actual starting line-ups and the starting line-ups predicted by *Kicker*. The left graph shows that 87 percent of the start players belong to the expected starting line-up. This overlap is reassuring because it suggests strong first-stage relationships. A concern might be that *Kicker* correctly predicts the actual starting line-up in most of the cases and makes serious mistakes in a few very specific cases. The right graph of Figure 2 addresses this issue. We show that *Kicker* correctly predicts the full starting line-up in only 23 percent of the cases and that the number of incorrect predictions per starting line-up is usually small.

4.2.2 Unexpected changes in birthplace diversity

Our second approach uses changes in birthplace diversity that result from unexpected changes in the starting line-ups. To produce our instrumental variable, we proceed in three steps. First, we distinguish between three groups of players (for an example, see Figure B.1). The first groups includes all players that belong to the starting line-up predicted by *Kicker* and are no start players ($\mathcal{A}$). The second group includes all start players that are not part of the expected starting line-up ($\mathcal{B}$). The last group includes all remaining start players ($\mathcal{C}$).

In the second step, we calculate the average dissimilarity between the players in $\mathcal{C}$ and $\mathcal{A}$ ($\mathcal{B}$):

$$\Delta(\mathcal{A},\mathcal{C}) = \frac{1}{|\mathcal{A}|} \cdot \frac{1}{|\mathcal{C}|} \cdot \sum_{j \in \mathcal{A}} \sum_{k \in \mathcal{C}} (1 - a_{jk}) \tag{16}$$

$$\Delta(\mathcal{B},\mathcal{C}) = \frac{1}{|\mathcal{B}|} \cdot \frac{1}{|\mathcal{C}|} \cdot \sum_{j \in \mathcal{B}} \sum_{k \in \mathcal{C}} (1 - a_{jk}) \tag{17}$$

where $a \in [0,1]$ is the similarity of the origin-specific characteristics of player j and player k. In the last step, we define the instrumental variable (Z) as the difference of $\Delta(\mathcal{B},\mathcal{C})$ and $\Delta(\mathcal{A},\mathcal{C})$:

$$Z = \Delta(\mathcal{B},\mathcal{C}) - \Delta(\mathcal{A},\mathcal{C}). \tag{18}$$

The variable Z is different from zero only if we observe an unexpected change in the starting line-up and if the players in $\mathcal{A}$ and $\mathcal{B}$ were not born in the same countries. Z is positive when the dissimilarity between the players that unexpectedly belonged to the starting line-up and the other start players ($\Delta(\mathcal{B},\mathcal{C})$) is larger than the dissimilarity between the players that unexpectedly dropped out from the starting line-up and the players that belonged to both the actual and the expected starting line-up ($\Delta(\mathcal{A},\mathcal{C})$).

Since we assume a hump-shaped relationship between birthplace diversity and team performance, we need to instrument both the measure of birthplace diversity and its squared term. Following Ashraf and Galor (2013), we use a three-stage procedure to address this issue.[21] In the first step, we perform a *zero-stage regression* in which the measure of birthplace diversity is regressed on the instrumental variable (Z) and the controls of the second-stage equation:

$$\text{BDiv}_{isrmd} = \phi \cdot Z_{isrmd} + \pi \cdot \mathbf{X}_{isrmd} + \xi_{isrm} + \theta_d + \nu_{isrmd}.^{22} \tag{19}$$

We then exploit the point estimates that we obtain when estimating (19) to calculate predicted values of birthplace diversity ($\widehat{BDiv}$). Finally, we use these predicted values and their squared terms as instruments. Taken together, we estimate the first-stage equations:[23]

$$\text{BDiv}_{isrmd} = \rho_1 \cdot \widehat{\text{BDiv}}_{isrmd} + \rho_2 \cdot \widehat{\text{BDiv}}^2_{isrmd} + \alpha \cdot \mathbf{X}_{isrmd} + \xi_{isrm} + \theta_d + \eta_{isrmd} \tag{20}$$

[21] For details about the econometric foundation of the procedure used by Ashraf and Galor (2013), see Angrist and Pischke (2009) and Wooldridge (2010). We require the zero-stage regression since Z^2 and $BDiv^2$ are only weakly correlated. The reason for this weak correlation is twofold: first, $Z \in [-1,1]$ and $BDiv \in [0,1]$ have different domains, and second, squaring is a non-monotonic transformation when the domain is $[-1,1]$, while it is a monotonic transformation when the domain is $[0,1]$.

[22] Figure B.3 shows the unconditional relationship of the birthplace diversity of a team ($BDiv$) and the instrumental variable Z. We observe a positive correlation between Z and $BDiv$. The correlation is 0.107 and statistically significant at the 1 percent level. This result is encouraging since it suggests a sound zero-stage relationship.

[23] It is irrelevant for the second-stage estimates of β_1, β_2, and $BDiv^*$ whether we use the variable Z or the predicted value $\widehat{BDiv}$ in the first-stage equations. Using $\widehat{BDiv}$ eases the interpretation of the reduced-form estimates.

$$\mathrm{BDiv}^2_{isrmd} = \delta_1 \cdot \widehat{\mathrm{BDiv}}_{isrmd} + \delta_2 \cdot \widehat{\mathrm{BDiv}}^2_{isrmd} + \lambda \cdot \mathbf{X}_{isrmd} + \xi_{isrm} + \theta_d + \mu_{isrmd}. \quad (21)$$

5 Results

5.1 Fixed effect estimates

In Table 1, we report our fixed effect estimates on the relationship between birthplace diversity and team performance. We exploit two different samples and two alternative measures of team performance. Columns 1 and 2 present results from estimating (13) when using the difference between goals scored and goals allowed as measure of team performance. In Columns 3 and 4, we measure team performance with the number of ranking points that the club obtains at the match. Columns 1 and 3 exploit the *full* sample which includes 7,038 Bundesliga matches. The *reduced* sample which is used in Columns 2 and 4 comprises 3,978 Bundesliga matches. The advantage of the *reduced* sample is that we can add the market value and the *FIFA score* to the list of control variable and thus control more efficiently for the quality of a team. We use standard errors robust against heteroscedasticity and clustered at the club-by-season-by-round-by-manager level.

The conventional method to test for the presence of a hump-shaped relationship is checking whether the estimate of the quadratic term of the variable of interest ($\hat{\beta}_2$) is negative and statistically significant at conventional levels. Lind and Mehlum (2010) argue that this common procedure is misleading if the optimal point is not within the lower and upper bound of the data range. Put differently, the point estimates of β_2 indicate whether the relationship between birthplace diversity and team performance is concave (Proposition 1a), but they do not show whether the optimal level of birthplace diversity is between 0 and 1 (Proposition 1b). Lind and Mehlum (2010) also develop a statistical test that addresses this problem. We apply this test and thus structure our regression tables in the following way. The upper part of the table shows the results of the Lind-Mehlum-Test, consisting of the estimated optimal level of birthplace diversity ($BDiv^*$) and a p-value that reveals the presence of a hump-shaped relationship within the data range. The lower part of the table presents the regression coefficients of the parameters β_1 and β_2 and their p-values.

Our fixed effect estimates provide only little evidence for a hump-shaped relationship between birthplace diversity and team performance. The regression coefficients of the parameter β_2 have the correct sign, but are not statistically significant at conventional levels in three out of four cases. The results of the Lind-Mehlum-Test suggest that the optimal level of birthplace diversity ($BDiv^*$) is not statistically different from zero and point to a negative rather than a hump-shaped effect of birthplace diversity on team performance.[24]

[24] Consistent with the results of the Lind-Mehlum-Test, we observe negative and statistically significant estimates of the parameter β_1 when excluding the squared term of the measure of birthplace diversity ($BDiv^2$) from the regression model (see Table C.3). This result fits together with other studies using

Table 1 Birthplace diversity and team performance: fixed effect estimates.

	Goal Difference		Points	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.148	0.138	0.234	0.273
	(0.387)	(0.430)	(0.224)	(0.246)
	Regression coefficients			
Diversity team (β_1)	0.310	0.259	0.552	0.738
	(0.774)	(0.861)	(0.449)	(0.492)
Diversity team squared (β_2)	-1.050	-0.938	-1.182**	-1.351
	(0.233)	(0.427)	(0.049)	(0.114)
Observations	14,076	7,956	14,076	7,956
Seasons	23	13	23	13
Quality controls	No	Yes	No	Yes

Notes: The table reports results from fixed effect regressions. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

5.2 Instrumental variable estimates

We argue that the fixed effect estimates presented in Table 1 underestimate the true optimal level of birthplace diversity because of reverse causality. Reverse causality is a problem because the substitutions that the team managers make during a match are endogenous to the performance of their team. Team managers increase the number of offensive players and decrease the number of defensive players if their team performs badly (Garicano and Palacios-Huerta, 2014). These changes often do not influence the outcome of a match, but they often increase birthplace diversity because the share of German offensive players is usually smaller than the share of German defensive players (for details, see Appendix A).

5.2.1 Diversity in expected starting line-up

We address endogeneity issues with two instrumental variable approaches. In our first approach, we exploit the starting line-ups predicted by the sports magazine *Kicker* and use the birthplace diversity in an expected starting line-up as the instrument for the birthplace diversity of the fielded players. Since *Kicker* publishes its expected starting line-up at least one day before a match begins, our approach allays any concern about reverse causality.

Columns 1 and 2 of Table 2 show the reduced-form estimates for our two measures of team performance. We have to restrict our analysis to the *reduced* sample because of limited data availability. The regression coefficients suggest a hump-shaped relationship

fixed effects models and data from sports industry to examine the effect of birthplace diversity on team performance (Haas and Nüesch, 2012, Kahane et al., 2013, Maderer et al., 2014). We believe that the estimates reported in Table C.3 are biased due to reverse causality (for details, see Appendix A).

Table 2 Birthplace diversity and team performance: 2SLS estimates (expected starting line-up).

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.588*	0.563*	0.609*	0.582*
	(0.067)	(0.058)	(0.072)	(0.062)
	Regression coefficients			
Diversity *Kicker*	1.793	1.27		
	(0.102)	(0.117)		
Diversity *Kicker* squared	-1.524*	-1.128*		
	(0.091)	(0.094)		
Diversity team (β_1)			5.339	3.795
			(0.103)	(0.123)
Diversity squared team (β_2)			-4.386*	-3.261*
			(0.093)	(0.100)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	125.52	125.52
SaWi F-statistic ($BDiv^2$)	-	-	287.19	287.19
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. The first-stage estimates are reported in Table C.4. We present the first-stage diagnostics proposed by Sanderson and Windmeijer (2016) and Stock and Wright (2000) in the bottom part of the table. Non of these tests indicate a weak instrument problem. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

between the birthplace diversity in the expected starting line-up and the performance of the fielded players. The results of the Lind-Mehlum-Test confirm this finding.

Columns 3 and 4 of Table 2 present the second-stage estimates. Consistent with the predictions of our stylized model (see Section 2), we find that an intermediate level of birthplace diversity maximizes the performance of a team. Our estimates also suggest that changing the birthplace diversity by 10 percentage points in either direction at the predicted optimal level (≈ 0.6) decreases the goal difference by 0.044, which is 3.149 percent of the sample mean.[25] Projected to the season as a whole, this amounts to a decrease in the goal difference by more than one goal.

5.2.2 Unexpected changes in diversity

Table 3 shows the results of our second instrumental variable approach. This approach exploits unexpected changes in the birthplace diversity of the start players to create a predicted value of the birthplace diversity of the fielded players and uses this predicted value (and its squared term) as an instrument for the actual birthplace diversity of the fielded players (for details, see Section 4.2.2).

[25] A change of 10 percentage points in birthplace diversity means that the probability that two randomly chosen team members have the same country of birth increases/decreases by 10 percentage points.

Table 3 Birthplace diversity and team performance: 2SLS estimates (unexpected changes).

	Reduced-form estimates		**Second-stage estimates**	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^{*}$)	0.721*	0.573	0.605**	0.586*
	(0.050)	(0.173)	(0.022)	(0.073)
	Regression coefficients			
$\widehat{BDiv}$	6.367**	2.375		
	(0.045)	(0.267)		
$\widehat{BDiv}^2$	-4.414**	-2.073		
	(0.024)	(0.126)		
Diversity team (β_1)			42.230**	19.154
			(0.044)	(0.147)
Diversity squared team (β_2)			-34.883**	-16.33
			(0.042)	(0.134)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	13.41	13.41
SaWi F-statistic ($BDiv^2$)	-	-	14.02	14.02
StWr p-value	-	-	0.000	0.002

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. The first-stage estimates are reported in Table C.5. We present the first-stage diagnostics proposed by Sanderson and Windmeijer (2016) and Stock and Wright (2000) in the bottom part of the table. Non of these tests indicate a weak instrument problem. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

The structure of Table 3 is the same as the structure of Table 2. Columns 1 and 2 present the reduced-form estimates, while Columns 3 and 4 report the second-stage estimates. All estimates are based on the *reduced* sample and we use two measures of team performance.

Table 3 shows that the reduced-form estimates vary slightly depending on how we measure performance. When using the goal difference (Column 1), we observe that the estimates have the expected sign and are statistically significant at conventional levels. The reduced-form estimates keep their signs if we apply the number of ranking points. However, their levels of statistical significance slightly decrease (Column 2). We think that these differences are plausible.[26]

The results of the second-stage regressions are consistent with the key predictions of our stylized model. The Lind-Mehlum-Tests confirm the existence of a hump-shaped relationship between birthplace diversity and team performance. Reassuringly, we find that the predicted optimal level of birthplace diversity closely resembles the predicted optimum reported in Table 2. The regression coefficients of β_1 and β_2 are statistically

[26]The number of ranking points often does not indicate performance differences even if they exist. For example, if a team loses a match zero to one, it receives the same number of ranking points as it would obtains if it loses zero to five. Due to this low distinctiveness, we argue that the number of ranking points is a less precise measure of team performance than the goal difference.

significant at the five percent levels when we measure team performance with the goal difference (Column 3). The p-values are slightly above ten percent when we use the number of ranking points (Column 4). The point estimates suggest that a change in birthplace diversity by 10 percentage points in either direction at the predicted optimal level decreases the difference between goals scored and goals allowed by 0.035.

5.3 Discussion

In Section 5.2, we report results from two-stage least squares regressions suggesting a hump-shaped relationship of birthplace diversity and team performance. This section presents a battery of robustness checks and investigates whether the optimal level of birthplace diversity varies depending on the importance of communication.

5.3.1 Injuries as source of variation

A concern may be that the discrepancies between the actual starting line-ups and the starting line-ups predicted by *Kicker* do not occur randomly. The estimates shown in Tables 2 and 3 are biased if the causes of the discrepancies are not captured by our control variables. We think that this is unlikely because of the comprehensive list of controls (see Table C.2) and the great number of fixed effects.

To strengthen the credibility of our results, we perform a robustness check that only exploits those discrepancies between the actual and the expected starting line-ups that are explainable with short-term injuries. We argue that the short-term injuries occur coincidentally and can thus be used to create plausibly exogenous variation in teams' composition.

We define that an injury serves as an explanation for a discrepancy in either of the following cases: (i) *Kicker* predicted that a player would be a starting player, but this player did not play since he was injured or did not completely recover from an injury. (ii) *Kicker* predicted that a player could not play because of an injury, but he was fit enough for attending the match. To identify the incorrect predictions that are caused by an injury, we analyzed articles and match reports published by *Kicker* and exploited the online database *Transfermarkt*. In total, injuries explain 30 percent of the incorrect predictions.

To exploit injuries to create exogenous variation in birthplace diversity, we slightly adjust the three-step procedure described in Section 4.2.2. The major change concerns the first step which classifies players into different groups. The first group ($\widetilde{\mathcal{A}}$) now includes players that belonged to the starting line-up predicted by *Kicker*, but did not attend to the match because of an injury. The second group ($\widetilde{\mathcal{B}}$) includes start players that were not part of the expected starting line-up and replaced an injured player. The third group ($\widetilde{\mathcal{C}}$) includes all other starting players (for an example, see Figure B.2).

The other steps of the procedure are the same as above. We calculate the average dissimilarity between the players in $\widetilde{\mathcal{C}}$ and $\widetilde{\mathcal{A}}$ ($\widetilde{\mathcal{B}}$):

$$\Delta(\widetilde{\mathcal{A}},\widetilde{\mathcal{C}}) = \frac{1}{|\widetilde{\mathcal{A}}|} \cdot \frac{1}{|\widetilde{\mathcal{C}}|} \cdot \sum_{j \in \widetilde{\mathcal{A}}} \sum_{k \in \widetilde{\mathcal{C}}} (1 - a_{jk}) \tag{22}$$

$$\Delta(\widetilde{\mathcal{B}},\widetilde{\mathcal{C}}) = \frac{1}{|\widetilde{\mathcal{B}}|} \cdot \frac{1}{|\widetilde{\mathcal{C}}|} \cdot \sum_{j \in \widetilde{\mathcal{B}}} \sum_{k \in \widetilde{\mathcal{C}}} (1 - a_{jk}). \tag{23}$$

and define the variable $\widetilde{Z}$ as the difference between $\Delta(\widetilde{\mathcal{B}},\widetilde{\mathcal{C}})$ and $\Delta(\widetilde{\mathcal{A}},\widetilde{\mathcal{C}})$:

$$\widetilde{Z} = \Delta(\widetilde{\mathcal{B}},\widetilde{\mathcal{C}}) - \Delta(\widetilde{\mathcal{A}},\widetilde{\mathcal{C}}).^{27} \tag{24}$$

We then run the *zero-stage regression* and use the estimated regression coefficients to compute predicted values of birthplace diversity ($\widetilde{BDiv}$), which serve—along with their squared terms—as the instrumental variables (for details, see Section 4.2.2).

Table C.6 illustrates that the signs of the regression coefficients of β_1 and β_2 are consistent with the predictions of our stylized model when using injuries as source of exogenous variation. We find that the estimates are statistically significant at the 10 percent level when we use the goal difference to as measure of team performance. The Lind-Mehlum-Test suggests that the optimal level of birthplace diversity is about 0.63, which is remarkably close to the figures reported in Tables 2 and 3. The predicted optimal level is 0.61 when we measure team performance with the number of ranking points. However, the estimate is not statistically significant at a standard level in this case (p-value: 0.264).

5.3.2 Alternative measures of birthplace diversity

The main challenge when computing an index of birthplace diversity is to specify the similarity matrix $\mathbf{A} = \{a_{ij}\}_{i,j=1,\ldots,n}$. Following Alesina et al. (2016), we use a binary similarity matrix: a_{ij} is equal to 1 if player i and player j were born in the same country, and is equal to 0 if these players come from different countries. To examine whether our main findings on the relationship between birthplace diversity and team performance change if we use a more distinctive similarity matrix, we exploit data on linguistic distance from Spolaore and Wacziarg (2016). Tables C.8 and C.9 indicate that our results are robust to this change in the similarity matrix.

5.3.3 Alternative definition of team

In our main analyses, a "team" includes all players that participated in a match for at least 1 minute. This approach may be criticized since it is debatable whether a player that is fielded for only a few minutes actually affects the performance of a team. As a robustness check, we thus count only those players as team members that played for

[27] Figure B.4 illustrates the unconditional relationship between the instrumental variable ($\widetilde{Z}$) and the birthplace diversity of the team ($BDiv$). The correlation of $\widetilde{Z}$ and $BDiv$ is 0.088 and statistically significant at the 1 percent level.

at least 30 minutes. Tables C.10 and C.11 illustrate that our results remain almost unchanged when using this alternative definition of "team".

5.3.4 Performance trends

The literature on sport science suggests that self-confidence is an important factor of success (Fletcher and Sarkar, 2012, Hays et al., 2009, Woodman and Hardy, 2003). In soccer, a major determinant of self-confidence is the performance in previous matches. Since our basic regression model does not control for past performance and unexpected changes in the starting line-ups might be correlated with past performance, our 2SLS estimates may be biased because of a violation of the exclusion restriction. To alleviate this concern, we add the first two lags of the dependent variable to the list of controls. Tables C.12 and C.13 suggest that this model extension does not lead to significant changes in our estimation results.

5.3.5 Migration

Anther concern may be that the country of birth differs from the country in which a player grew up. The 2SLS estimates shown in Tables 2 and 3 would be biased if such discrepancies produce a non-classical measurement error in the measure of birthplace diversity. To alleviate this concern, we identified for each player the country where he lived during his youth. The web database *Transfermarkt* served as our main source of information and we found that this country differs from the country of birth for 6.5 percent of the players. Tables C.14 and C.15 show that our 2SLS estimates do not significantly change when we exploit the countries where the players lived during their youth to measure birthplace diversity.

5.3.6 Alternative procedure for measuring unexpected changes

In our basic approach, we distinguish between three groups of players and use a three-stage procedure to create an instrumental variable (Z) that reflects unexpected changes in birthplace diversity (see Section 4.2.2). An alternative approach is to calculate the difference of the birthplace diversity in the actual starting line-up and the birthplace diversity in the starting line-up predicted by *Kicker*. Table C.16 presents estimation results suggesting that we obtain similar estimates for the optimal level of birthplace diversity when applying the alternative procedure for measuring unexpected changes in birthplace diversity. We prefer our basic approach for two reasons: first, the first-stage F-statistics are slightly higher, and second, it is easier to restrict the analysis to those unexpected changes that are caused by injuries.

5.3.7 Linear model

The related literature includes some studies that use data from the professional sports industry and fixed effect models to examine the effect of birthplace diversity on team performance. Most of these studies find that the negative effects of birthplace diversity outweigh the positive effects (see Haas and Nüesch, 2012, Kahane et al., 2013, Maderer et al., 2014). Table C.3 shows that our fixed effect results point in the same direction if we exclude the squared term of birthplace diversity from the regression model. Our instrumental variable estimates, however, do not suggest a linear relationship between birthplace diversity and team performance (see Tables C.17 and C.18).

5.3.8 Piecewise regression approach

The estimates reported in Table 2 and 3 suggest that the optimal level of birthplace diversity ($BDiv^*$) is around 0.6. This implies that an increase in birthplace diversity ($BDiv$) improves (reduces) team performance if $BDiv$ is smaller (larger) than $BDiv^*$. Put differently, if we estimate a linear regression model and restrict the sample to the observations with $BDiv < BDiv^*$ ($BDiv > BDiv^*$), we should find that birthplace diversity positively (negatively) affects team performance. Columns 1 and 2 of Table C.19 illustrates that this is indeed the case, if the birthplace diversity in the starting line-up predicted by *Kicker* serves as the instrumental variable.

Combining the piecewise regression approach with our second instrumental variable approach is slightly more difficult because it exploits changes in birthplace diversity to create plausibly exogenous variation. Assume that the actual birthplace diversity of a team exceeds the optimal level ($BDiv > BDiv^*$) and that an unexpected change in birthplace diversity occurs ($Z \neq 0$). If this change is positive (negative), birthplace diversity moves away from (towards) the optimal level. We therefore expect a negative (positive) estimate when estimating the linear model and restricting the sample to the observations with Z larger (smaller) than 0. Columns 3 and 4 of Table C.19 confirm this expectation.[28]

5.3.9 Heterogeneity in the optimal level of birthplace diversity

The key prediction of the model developed in Section 2 is that an intermediate level of birthplace diversity maximizes the performance of a working group. The results of our empirical analyses confirm this prediction. Our simple model also predicts that the optimal level of birthplace diversity varies depending on how important it is that team members effectively communicate with each other (see Proposition 1c). In this section, we examine the accuracy of this prediction.

The performance of a soccer team has two key components: scoring goals (offensive performance) and preventing goals (defensive performance). Because communication is less important in the offense than in the defense, we expect that the optimal level of birthplace diversity is lower for defensive performance than for offensive performance. The estimation results reported in Table C.20 are consistent with our expectations. In Column 1, we examine the effect of birthplace diversity and offensive performance. We

[28]We cannot conduct this robustness check for the case $BDiv < BDiv^*$ because the sample size is too small.

assume that midfielders and forwards are responsible for the offense and thus use the birthplace diversity of these players as explanatory variable. The birthplace diversity of the midfielders and forwards in the starting line-up predicted by *Kicker* serves as our instrumental variable.[29] Our regression coefficients suggests that the optimal level of birthplace diversity for offensive performance is around 0.65. Column 2 indicates that the optimal level of birthplace diversity for defensive performance is considerably lower (0.5). In this case, the explanatory variable is the birthplace diversity of the defenders and midfielders.

6 Conclusion

Since multinational working groups have become more prevalent in almost all advanced economies, understanding how birthplace diversity affects the performance of a team is highly important. This paper presents a simple model to illustrate that this effect is hump-shaped if collaboration requires verbal communication and if team members born in different countries have complementary abilities. To examine the accuracy of this prediction, we exploit self-collected data from the Bundesliga, the highest division of German male soccer. Our data covers 23 seasons and includes detailed information on 3,266 players coming from 98 countries. We illustrate that the fixed effect estimator underestimates the true optimal level of birthplace diversity, especially due to reverse causality, and address endogeneity problems with two instrumental variable approaches. The first approach exploits the birthplace diversity in a predicted line-up to produce plausibly exogenous variation in the birthplace diversity of the fielded players, whereas the second approach uses unexpected last-minute changes in the birthplace diversity of the starting players as source of exogenous variation. The results of our instrumental variable regressions imply that the effect of birthplace diversity on team performance is hump-shaped. The predicted optimal level of birthplace diversity is 0.6.

Our study is the first to identify a causal non-linear relationship between birthplace diversity and team performance. We thus provide clear evidence for the existence of a trade-off between the beneficial and the adverse effects of diversity on productivity (Alesina and La Ferrara, 2005, Lazear, 1999): while homogeneous teams do not have sufficient diversity in perspectives and skills, highly heterogeneous work groups cannot effectively communicate and therefore suffer from coordination problems.

A concern may be that professional soccer is a rather special industry and that the external validity of our results is thus low. We argue that this is not the case since effective interaction and diversity in skills are both factors for success in various fields. Examples include: research and development, arts and music, consultancy, marketing, and other creative professions. However, our model suggests that the optimal level of birthplace diversity is likely to differ between and within these working fields. We also

[29] We cannot use our second instrumental variable approach since the first-stage diagnostics indicate a weak instrument problem.

provide empirical evidence confirming that the optimal level of birthplace diversity is task-specific.[30]

Finding the optimal levels of birthplace diversity in other working fields should be a key objective of future research. Another pending issue is whether the optimal level of birthplace diversity varies depending on other characteristics of the team, such as age, tenure, or quality. Finally, there still exists a lack of causal evidence on the channels through which birthplace diversity affects team performance.

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[30] The effect of birthplace diversity on team performance might no be hump-shaped in any case. If, for example, people coming from different countries do not differ in their productive skills, our model predicts that team performance decreases in the level of birthplace diversity. This prediction is consistent with the results of Lyons (2017) who conducted a field experiment with web programmers and observed that the nationally diverse teams were less successful than the nationally homogeneous teams because of communication problems.

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A Additional information on the fixed effect model

Although our basic regression model (see (13)) includes a rich set of fixed effects and various control variables, we argue that this model is unsuited for an analysis of the relationship between birthplace diversity and team performance. We are convinced that the fixed effect estimator underestimate the optimal level of birthplace diversity due to reverse causality. This section presents results that substantiate our claim.

Our analysis consists of three parts. The first part shows how team managers react during a match if the performance of their team is low. To address this question, we divide each match into eighteen non-overlapping five-minute periods and estimate the regression model:

$$\mathrm{O}^{e}_{isrmdp} = \alpha \cdot \mathrm{O}^{b}_{isrmdp} + \beta \cdot \mathrm{B}^{b}_{isrmdp} + \gamma \cdot \mathbf{X}^{b}_{isrmdp} + \xi_{isrmd} + \theta_p + \varepsilon_{isrmdp} \tag{A1}$$

where i is a club, s a season, m a manager, d a match day, r a round, and p a five-minute period. O^b/O^e is the number of fielded offensive players (forwards) at the beginning/end of a period. B is a dummy variable that is equal to 1 if the team is behind at the beginning of the period p. The vector $\mathbf{X}$ includes team and opponent controls. ξ is the team-by-match fixed effect, θ the period fixed effect, and ε an error term.

Table C.21 presents results from estimating (A1). Column 1 uses the *full* sample. Column 2 exploits the reduced sample and controls for the quality of fielded players. Consistent with the findings of Garicano and Palacios-Huerta (2014), we observe that team managers increase the number of fielded forwards if their team is behind.

The second part of our analysis studies whether birthplace diversity varies with the score of a match. We address this issue with the regression model:

$$\mathrm{D}^{e}_{isrmdp} = \alpha \cdot \mathrm{D}^{b}_{isrmdp} + \beta \cdot \mathrm{B}^{b}_{isrmdp} + \gamma \cdot \mathbf{X}^{b}_{isrmdp} + \xi_{isrmd} + \theta_p + \varepsilon_{isrmdp} \tag{A2}$$

where D^b/D^e is the level of birthplace diversity at the beginning/end of a five-minute period. The other components of (A2) have the same meaning as in (A1).

Table C.22 reports results from estimating (A2). We find that birthplace diversity increases during a match if a team is behind regardless of whether we exploit the *full* sample (see Column 1) or the *reduced* sample (see Column 2).

The last part of our analysis provides an explanation for why low team performance causes an increase in birthplace diversity. There are two reasons: first, team managers dislike losses and thus replace defensive players with offensive players if their team is behind (see Table C.21), and second, the share of foreigners in German soccer clubs is much larger among offensive players than among defensive players. Put differently, we argue that the increase in the number of forwards is the channel through which team performance affects birthplace diversity.[31] The estimation results shown in Table C.23 support this argument. We find that the estimate of the effect of team performance on birthplace diversity becomes statistically insignificant when we extent regression model (A2) by the number of fielded offensive players at the end of a five-minute period.

B Additional figures

Figure B.1 Classification of players: Baseline approach (example)

Predicted Line-up	**Starting Line-up**
Ulreich	Ulreich
Kimmich Süle Hummels Alaba	Kimmich Süle Hummels Rafinha
Martinez Thiago James	Tolisso Thiago James
Müller Lewandowski Ribery	Müller Lewandowski Ribery

Notes: The left panel shows the expected starting line-up of *Bayern München* for the match on Saturday, 12th May 2018. *Kicker* published this line-up on Friday, 11th May 2018. The right panel shows the actual starting line-up. We use *blue* characters to indicate players (Alaba, Martinez) that belong to group $\mathcal{A}$, *red* characters to indicate players (Rafinha, Tolisso) that belong to group $\mathcal{B}$, and *black* characters to indicate players that belong to group $\mathcal{C}$.

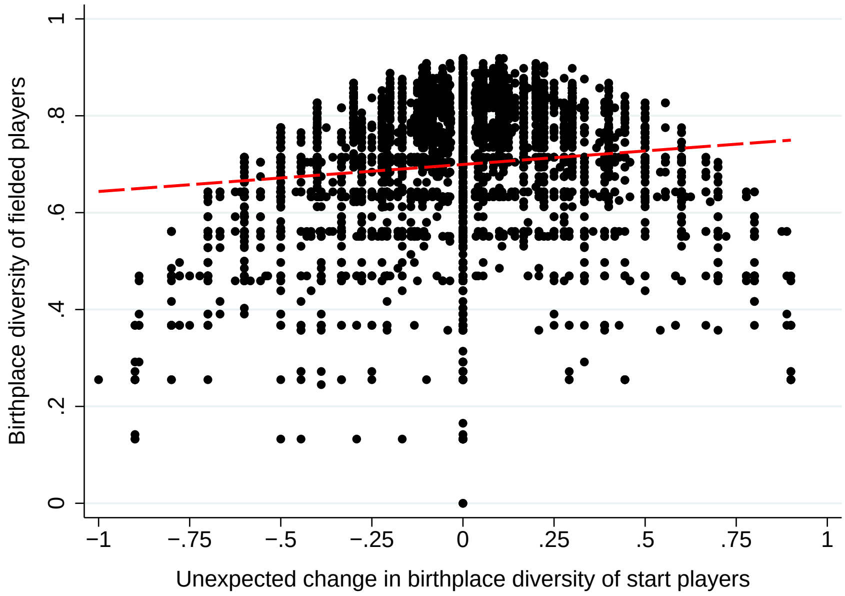
Figure B.2 Classification of players; Alternative approach (example)

Predicted Line-up	**Starting Line-up**
Ulreich	Ulreich
Kimmich Süle Hummels Alaba	Kimmich Süle Hummels Rafinha
Martinez Thiago James	Tolisso Thiago James
Müller Lewandowski Ribery	Müller Lewandowski Ribery

Notes: The left panel shows the expected starting line-up of *Bayern München* for the match on Saturday, 12th May 2018. *Kicker* published this line-up on Friday, 11th May 2018. The right panel shows the actual starting line-up. We use *blue* characters to indicate players (Alaba) that belong to group $\widetilde{\mathcal{A}}$, *red* characters to indicate players (Rafinha) that belong to group $\widetilde{\mathcal{B}}$, and *black* characters to indicate players that belong to group $\widetilde{\mathcal{C}}$. Players (Martinez) colored in *violet* belong to neither of the three groups. David Alaba belongs to group $\widetilde{\mathcal{A}}$ because he unexpectedly missed the match because of back problems.

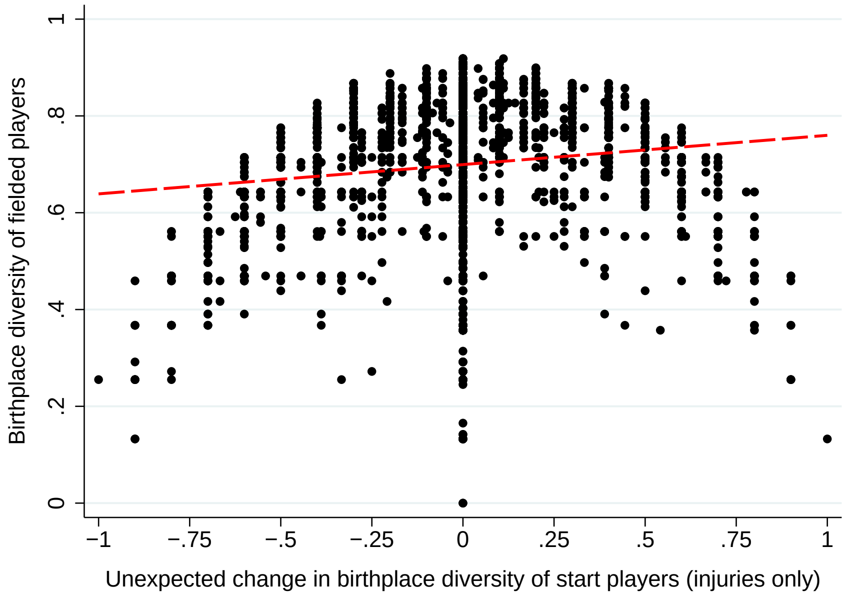
[31]Our data suggests that the share of foreign defenders and foreign midfielders is around 45 percent, whereas the share of foreign forwards is around 65 percent.

Figure B.3 Unconditional zero-stage relationship (all unexpected changes).



Notes: The figure depicts the positive correlation between the birthplace diversity of a team ($BDiv$) and our instrumental variable Z as defined in (18). The correlation coefficient is 0.107 and statistically significant at the 1 percent level.

Figure B.4 Unconditional zero-stage relationship (only unexpected changes caused by injuries).



Notes: The figure depicts the positive correlation between the birthplace diversity of a team ($BDiv$) and our instrumental variable $\widetilde{Z}$ as defined in (24). The correlation coefficient is 0.088 and statistically significant at the 1 percent level.

C Additional tables

Table C.1 List of countries.

Country	Country	Country
Albania (13)	Gambia (3)	Norway (36)
Algeria (1)	Georgia (9)	Paraguay (5)
Argentina (36)	Germany (1534)	Peru (6)
Armenia (1)	Ghana (26)	Poland (89)
Australia (16)	Greece (19)	Portugal (16)
Austria (71)	Guinea (3)	Romania (28)
Azerbaijan (1)	Guinea-Bissau (2)	Russia (16)
Belarus (3)	Hungary (27)	Senegal (11)
Belgium (38)	Iceland (6)	Serbia (47)
Benin (2)	Iran (10)	Sierra Leone (3)
Bolivia (1)	Israel (5)	Slovakia (23)
Bosnia and Herzegovina (35)	Italy (13)	Slovenia (14)
Brazil (141)	Ivory Coast (12)	South Africa (11)
Bulgaria (24)	Jamaica (2)	Spain (38)
Burkina Faso (3)	Japan (28)	Suriname (4)
Cameroon (25)	Kazakhstan (5)	Sweden (39)
Canada (9)	Korea (11)	Switzerland (79)
Cape Verde (1)	Kosovo (17)	Syria (1)
Chile (8)	Latvia (2)	Tajikistan (3)
China (3)	Lebanon (2)	Togo (4)
Colombia (8)	Liechtenstein (1)	Trinidad and Tobago (1)
Congo Demo. Rep. (12)	Lithuania (1)	Tunisia (10)
Cong Rep. (4)	Luxembourg (2)	Turkey (17)
Costa Rica (1)	Macedonia (16)	Ukraine (20)
Croatia (71)	Mali (2)	United Kingdom (15)
Cyprus (1)	Malta (1)	United States (32)
Czech Republic (70)	Mexico (8)	Uruguay (7)
Denmark (75)	Moldova (2)	Venezuela (5)
Ecuador (3)	Montenegro (9)	Zambia (3)
Egypt (7)	Morocco (8)	Zimbabwe (1)
Equatorial Guinea (3)	Mozambique (1)	
Estonia (1)	Namibia (2)	
Finland (12)	Netherlands (72)	
France (92)	Nigeria (26)	

Notes: This table lists the countries from which the players in our sample originate. In parenthesis, we report the number of players born in a particular country.

Table C.2 List of control variables ($\mathbf{X}$).

Variable	Description
Home	Dummy variable that is equal to 1 if a team had the home field advantage.
Cup$^{(a)}$	Dummy variable that is equal to 1 if a team played in the national cup in the week before (or the week after) a *Bundesliga* match.
ECT$^{(a)}$	Dummy variable that is equal to 1 if a team played in an European club tournament in the week before (or the week after) a *Bundesliga* match.
Age$^{(\mathrm{a,b})}$	Average age (in years).
Tenure$^{(\mathrm{a,b})}$	Average duration of club membership (in years).
Bundesliga matches$^{(\mathrm{a})}$	Average number of *Bundesliga* matches.
European matches$^{(\mathrm{a})}$	Average number of matches in European club tournaments.
Championship matches$^{(\mathrm{a})}$	Average number of matches in European and World Championship matches.
Top-League matches$^{(\mathrm{a})}$	Average number of matches in highest soccer divisions in England, France, Italy, and Spain.
Market value$^{(\mathrm{a,c})}$	Average of logged market value.
FIFA score$^{(\mathrm{a,c})}$	Average playing strength in video game FIFA.
Age (manager)$^{(\mathrm{a})}$	Age of the manager.
Membership (manager)$^{(\mathrm{a})}$	Number of years in which the manager was in charge of the team.
Bundesliga matches (manager)$^{(\mathrm{a})}$	Total number of Bundesliga matches that a manager was in charge of a *Bundesliga* team.
Opponent-Season fixed effects	Set of season-specific dummy variables that indicate the opponent of the team.
Ranking fixed effects	Set of dummy variables that capture the current ranking positions of the opposing teams.

Notes: This table lists all variables that are included in the vector $\mathbf{X}$. (a) indicates that $\mathbf{X}$ includes this variable for both the team and its opponent. (b) indicates that $\mathbf{X}$ includes the squared term of the variable. (c) indicates that $\mathbf{X}$ does not include this variable if we use the full sample.

Table C.3 Birthplace diversity and team performance: fixed effect estimates (linear model).

	Goal Difference		**Points**	
	(1)	(2)	(3)	(4)
Diversity (β_1)	-0.905***	-0.876**	-0.819***	-0.905***
	(0.002)	(0.021)	(0.000)	(0.001)
Observations	14,076	7,956	14,076	7,956
Seasons	23	13	23	13
Quality controls	No	Yes	No	Yes

Notes: The table reports results from fixed effect regressions. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.4 First-stage estimates (expected starting line-up).

	(1)	(2)
Diversity *Kicker*	0.363***	0.033
	(0.000)	(0.537)
Diversity *Kicker* squared	-0.030	0.311***
	(0.553)	(0.000)
Observations	7,956	7,956
Seasons	13	13
Dependent Variable	$BDiv$	$BDiv^2$
SaWi F-statistic	125.52	287.19

Notes: The table reports first-stage estimates. For the corresponding second-stage estimates, see Table 2. Standard errors are clustered at the club-by-season-by-round-by-manager level and p-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.5 Zero-stage and first-stage estimates (unexpected changes).

	Zero-stage estimates	**First-stage estimates**	
	(1)	(2)	(3)
$\Delta(\mathcal{B},\mathcal{C}) - \Delta(\mathcal{A},\mathcal{C})$	0.0457***		
	(0.000)		
$\widehat{BDiv}$		0.984***	1.009***
		(0.000)	(0.000)
$\widehat{BDiv}^2$		0.011	0.140
		(0.898)	(0.197)
Observations	7,956	7,956	7,956
Seasons	13	13	13
Dependent Variable	$BDiv$	$BDiv$	$BDiv^2$
SaWi F-statistic	-	13.41	14.02

Notes: The table reports zero-stage and first-stage estimates. For the corresponding second-stage estimates, see Table 3. Standard errors are clustered at the club-by-season-by-round-by-manager level and p-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.6 Birthplace diversity and team performance: 2SLS estimates (unexpected changes, injuries)

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^{*}$)	0.688	0.527	0.631**	0.613
	(0.115)	(0.388)	(0.049)	(0.264)
	Regression coefficients			
$\widetilde{BDiv}$	5.038	0.968		
	(0.158)	(0.705)		
$\widetilde{BDiv}^{2}$	-3.661*	-0.918		
	(0.063)	(0.520)		
Diversity team (β_1)			42.169*	10.14
			(0.097)	(0.529)
Diversity squared team (β_2)			-33.425*	-8.274
			(0.091)	(0.513)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	9.68	9.68
SaWi F-statistic ($BDiv^2$)	-	-	10.14	10.14
StWr p-value	-	-	0.000	0.347

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.7 Zero-stage and first-stage estimates (unexpected changes, injuries).

	Zero-stage estimates	First-stage estimates	
	(1)	(2)	(3)
$\Delta(\widetilde{\mathcal{B}},\widetilde{\mathcal{C}}) - \Delta(\widetilde{\mathcal{A}},\widetilde{\mathcal{C}})$	0.0459***		
	(0.000)		
$\widetilde{BDiv}$		0.946***	1.042***
		(0.000)	(0.000)
$\widetilde{BDiv}^{2}$		0.038	0.158
		(0.681)	(0.169)
Observations	7,956	7,956	7,956
Seasons	13	13	13
Dependent Variable	$BDiv$	$BDiv$	$BDiv^2$
SaWi F-statistic	-	9.68	10.14

Notes: The table reports zero-stage and first-stage estimates. For the corresponding second-stage estimates, see Table C.6. Standard errors are clustered at the club-by-season-by-round-by-manager level and p-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.8 Alternative measure of birthplace diversity (expected starting line-up).

	Reduced-form estimates		**Second-stage estimates**	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.549**	0.543**	0.567**	0.560**
	(0.027)	(0.034)	(0.028)	(0.035)
	Regression coefficients			
Diversity *Kicker*	2.368**	1.601*		
	(0.042)	(0.059)		
Diversity *Kicker* squared	-2.168**	-1.476**		
	(0.035)	(0.048)		
Diversity team (β_1)			6.994**	4.709*
			(0.040)	(0.056)
Diversity squared team (β_2)			-6.171**	-4.201**
			(0.034)	(0.047)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	151.61	151.61
SaWi F-statistic ($BDiv^2$)	-	-	302.56	302.56
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.9 Alternative measure of birthplace diversity (unexpected changes).

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.704*	0.594	0.569**	0.558*
	(0.087)	(0.132)	(0.041)	(0.072)
	Regression coefficients			
$\widehat{BDiv}$	6.481**	2.770		
	(0.044)	(0.195)		
$\widehat{BDiv}^2$	-4.600**	-2.331		
	(0.035)	(0.116)		
Diversity team (β_1)			52.93*	26.258
			(0.076)	(0.145)
Diversity squared team (β_2)			-46.490*	-23.511
			(0.077)	(0.140)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	7.23	7.23
SaWi F-statistic ($BDiv^2$)	-	-	7.35	7.35
StWr p-value	-	-	0.000	0.002

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.10 Alternative definition of team (expected starting line-up).

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^{*}$)	0.541**	0.516*	0.549**	0.524*
	(0.045)	(0.055)	(0.045)	(0.058)
	Regression coefficients			
Diversity *Kicker*	1.909*	1.313		
	(0.091)	(0.109)		
Diversity *Kicker* squared	-1.766*	-1.274*		
	(0.057)	(0.064)		
Diversity team (β_1)			4.413	3.035
			(0.089)	(0.116)
Diversity squared team (β_2)			-4.021*	-2.895*
			(0.056)	(0.068)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	161.87	161.87
SaWi F-statistic ($BDiv^2$)	-	-	326.46	326.46
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.11 Alternative definition of team (unexpected changes).

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.641**	0.520*	0.567**	0.555*
	(0.013)	(0.093)	(0.031)	(0.073)
	Regression coefficients			
$\widehat{BDiv}$	3.838**	1.517		
	(0.029)	(0.199)		
$\widehat{BDiv}^2$	-2.994***	-1.458*		
	(0.009)	(0.068)		
Diversity team (β_1)			34.266*	16.591
			(0.062)	(0.145)
Diversity squared team (β_2)			-30.221*	-14.941
			(0.057)	(0.134)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	9.20	9.20
SaWi F-statistic ($BDiv^2$)	-	-	9.59	9.59
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.12 Performance trend (expected starting line-up)

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.578*	0.553*	0.599*	0.574*
	(0.076)	(0.066)	(0.078)	(0.073)
	Regression coefficients			
Diversity *Kicker*	1.895	1.386		
	(0.121)	(0.132)		
Diversity *Kicker* squared	-1.639	-1.252		
	(0.107)	(0.102)		
Diversity team (β_1)			6.047	4.435
			(0.126)	(0.145)
Diversity squared team (β_2)			-5.046	-3.862
			(0.112)	(0.114)
Observations	6,815	6,815	6,815	6,815
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	96.90	96.90
SaWi F-statistic ($BDiv^2$)	-	-	222.36	222.36
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2), club-by-season-by-round-by-manager fixed effects, and the first and second lag of the dependent variable. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.13 Performance trend (unexpected changes)

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.440	0.194	0.572*	0.546
	(0.223)	(0.378)	(0.079)	(0.112)
	Regression coefficients			
$\widehat{BDiv}$	2.193	0.552		
	(0.443)	(0.767)		
$\widehat{BDiv}^2$	-2.494	-1.423		
	(0.115)	(0.176)		
Diversity team (β_1)			26.062	14.296
			(0.158)	(0.223)
Diversity squared team (β_2)			-22.774	-13.101
			(0.133)	(0.178)
Observations	6,815	6,815	6,815	6,815
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	11.22	11.02
SaWi F-statistic ($BDiv^2$)	-	-	11.85	11.61
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2), club-by-season-by-round-by-manager fixed effects, and the first and second lag of the dependent variable. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.14 Alternative definition of country of origin (expected starting line-up).

	Reduced-form estimates		**Second-stage estimates**	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^*$)	0.638*	0.594*	0.658*	0.612*
	(0.074)	(0.058)	(0.085)	(0.063)
	Regression coefficients			
Diversity *Kicker*	2.250**	1.467**		
	(0.014)	(0.033)		
Diversity *Kicker* squared	-1.765**	-1.234**		
	(0.029)	(0.043)		
Diversity team (β_1)			7.046**	4.636**
			(0.013)	(0.033)
Diversity squared team (β_2)			-5.350**	-3.786**
			(0.030)	(0.044)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	129.87	129.87
SaWi F-statistic ($BDiv^2$)	-	-	263.65	263.65
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.15 Alternative definition of country of origin (unexpected changes)

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^{*}$)	0.409	0.259	0.538**	0.523
	(0.253)	(0.429)	(0.038)	(0.141)
	Regression coefficients			
$\widehat{BDiv}$	2.028	0.511		
	(0.382)	(0.748)		
$\widehat{BDiv}^{2}$	-2.479*	-0.988		
	(0.054)	(0.270)		
Diversity team (β_1)			25.110*	9.980
			(0.076)	(0.282)
Diversity squared team (β_2)			-23.336	-9.540
			(0.063)	(0.248)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	14.41	14.41
SaWi F-statistic ($BDiv^2$)	-	-	15.35	15.35
StWr p-value	-	-	0.000	0.020

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.16 Alternative procedure for measuring unexpected changes in birthplace diversity

	Reduced-form estimates		**Second-stage estimates**	
	(1)	(2)	(3)	(4)
	Lind-Mehlum-Test			
Optimal diversity ($BDiv^{*}$)	0.629*	0.524	0.594**	0.581*
	(0.050)	(0.206)	(0.020)	(0.077)
	Regression coefficients			
$\widehat{BDiv}$	5.939*	2.206		
	(0.059)	(0.302)		
$\widehat{BDiv}^2$	-4.723**	-2.106		
	(0.018)	(0.126)		
Diversity team (β_1)			45.242**	19.731
			(0.040)	(0.153)
Diversity squared team (β_2)			-38.070**	-16.975
			(0.035)	(0.136)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic ($BDiv$)	-	-	12.79	12.79
SaWi F-statistic ($BDiv^2$)	-	-	13.20	13.20
StWr p-value	-	-	0.000	0.000

Notes: The table reports reduced-form estimates and second-stage estimates. The upper part of the table shows the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.17 Linear model (expected starting line-up).

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Regression coefficients			
Diversity *Kicker*	0.020	-0.047		
	(0.946)	(0.827)		
Diversity team (β_1)			0.061	-0.144
			(0.944)	(0.822)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic	-	-	641.13	641.13

Notes: The table reports reduced-form estimates and second-stage estimates. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.18 Linear model (unexpected changes).

	Reduced-form estimates		Second-stage estimates	
	(1)	(2)	(3)	(4)
	Regression coefficients			
$\Delta(\mathcal{B},\mathcal{C}) - \Delta(\mathcal{A},\mathcal{C})$	0.010	-0.024		
	(0.895)	(0.654)		
Diversity team (β_1)			0.226	-0.516
			(0.893)	(0.644)
Observations	7,956	7,956	7,956	7,956
Seasons	13	13	13	13
Outcome	Goal Diff.	Points	Goal Diff.	Points
SaWi F-statistic	-	-	263.92	263.92

Notes: The table reports reduced-form estimates and second-stage estimates. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.19 Piecewise linear regression approach.

	Expected line-up		Unexpected changes	
	(1)	(2)	(3)	(4)
	Regression coefficients			
Diversity team (β_1)	4.016**	-2.993*	-17.533*	20.083***
	(0.027)	(0.075)	(0.064)	(0.003)
Observations	2,139	5,817	1,737	1,325
Seasons	13	13	13	13
Outcome	Goal Diff.	Goal Diff.	Goal Diff.	Goal Diff.
SaWi F-statistic	95.44	384.53	14.18	28.67
Diversity level ($BDiv$)	< 0.6	> 0.6	> 0.6	> 0.6
Change in Diversity (Z)	-	-	> 0.0	< 0.0

Notes: The table reports second-stage estimates. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.20 Heterogeneity in optimal level of birthplace diversity.

	Performance in offense	Performance in defense
	(1)	(2)
	Lind-Mehlum-Test	
Optimal diversity ($BDiv^*$)	0.676	0.503
	(0.228)	(0.106)
	Regression coefficients	
Diversity team (β_1)	2.570*	-2.913
	(0.087)	(0.211)
Diversity squared team (β_2)	-1.901	2.896
	(0.164)	(0.134)
Observations	7,956	7,956
Seasons	13	13
Outcome	Goals scored	Goals allowed
SaWi F-statistic ($BDiv$)	151.46	185.85
SaWi F-statistic ($BDiv^2$)	286.82	359.96
StWr p-value	0.001	0.002
Team	Midfielder + Forwards	Defender + Midfielder

Notes: The table shows second-stage estimates. The upper part reports the results of the Lind-Mehlum-Test, the lower part presents regression coefficients. All regressions include team, manager, and opponent characteristics (for a list, see Table C.2) and club-by-season-by-round-by-manager fixed effects. We cluster standard errors at the club-by-season-by-round-by-manager level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.21 Effect of team performance on number of fielded offensive players (within-match variation).

	(1)	(2)
Behind at the beginning of a period	0.070***	0.074***
	(0.000)	(0.000)
Observations	253,368	143,208
Seasons	23	13
Quality controls	No	Yes
R^2	0.933	0.937

Notes: The table reports estimates from a dynamic fixed effect model. The dependent variable is the number of forwards on the field at the end of a five-minute period. All regressions include team and opponent controls and a set of team-by-match fixed effects. We cluster standard errors at the team-by-match level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.22 Effect of team performance on birthplace diversity (within-match variation).

	(1)	(2)
Behind at the beginning of a period	0.001***	0.001***
	(0.000)	(0.004)
Observations	253,368	143,208
Seasons	23	13
Quality controls	No	Yes
R^2	0.978	0.975

Notes: The table reports estimates from a dynamic fixed effect model. The dependent variable is the birthplace diversity of the players on the field at the end of a five-minute period. All regressions include team and opponent controls and a set of team-by-match fixed effects. We cluster standard errors at the team-by-match level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.23 Channel through which team performance affects birthplace diversity (within-match variation).

	(1)	(2)
Behind at the beginning of a period	-0.000	-0.000
	(0.804)	(0.456)
Fielded forwards at the end of a period	0.017***	0.016***
	(0.000)	(0.000)
Observations	253,368	143,208
Seasons	23	13
Quality controls	No	Yes
R^2	0.978	0.975

Notes: The table reports estimates from a dynamic fixed effect model. The dependent variable is the birthplace diversity of the players on the field at the end of a five-minute period. All regressions include team and opponent controls and a set of team-by-match fixed effects. We cluster standard errors at the team-by-match level and report p-values in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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