PhD-FDEF-2022-022
The Faculty of Law, Economics and Finance

DISSERTATION

Defence held on 16/11/2022 in Luxembourg
to obtain the degree of

Docteur de l'université du Luxembourg en sciences économiques

by

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Essays on the Economics of International Migration

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Acknowledgements

This thesis is the fruit of a journey I started four years ago as a PhD student, at the Department of Economics and Management of the University of Luxembourg. Several people had a crucial role in supporting my experience and this thesis. I feel privileged and deeply thankful for the impact they had on this path, and for the precious moments I will jealously hold in my memories. I would like to express my most sincere gratitude to my thesis advisor, professor Michel Beine, for all he's done in these years. Michel has been and is a reference and role model. His open-mindedness and positive attitude led me to feel comfortable in sharing my ideas. His patience made my progress smoother. His intellectual inputs made me challenge my knowledge. I am also deeply thankful to professor Nicolas Debarsy, for his kindness and availability during my stay at the University of Namur. It was great to receive his expertise and insights and to be given the chance to interact with him. I would like to also share my heartfelt gratitude to professor Skerdilajda Zanaj. She has had a significant, key role in my progress. I am deeply grateful for her availability, kindness, patience, for sharing with me her great expertise that I deeply admire, for being such a reference for many female students and young scholars.

A big thanks also goes to all my Ph.D. and post-doc colleagues for their support, motivation and friendship; in particular, Agnese, Aleksa, Alessio, Ana Cecilia, Andrej, Ariane, Basheer, Camila, Clotilde, Dara, Etienne, Giuseppe, Joachim, Ksenia, Maria, Melissa, Maxime, Mélanie, Nijat, Nora, Raian, Ruth, Sofia, Véronique, Nikita. Among them, I'd like to single out my unreplaceable office mate and precious friend Dr. Rana Comertpay, for all she's done to make my days better. I am also very thankful to Roswitha, Noémie, Chloé, Elisa, Anne-Sophie and Marina for their presence, availability and support with all the administrative tasks, and to all my professors at the department of Economics and Management of the University of Luxembourg. It was great taking this journey under their guidance, following their courses, having their insights during my presentations. In addition, I am also deeply thankful to professor Konstantinos Tatsiramos and to professor Philippe Van Kerm, who have been part of my thesis committee. Their insights were crucially valuable, and their availability highly appreciated. I would like to particularly thank professors Simone Bertoli and Hillel Rapoport, who kindly accepted to be part of my Ph.D. external jury. I am honored to receive their feedback and grateful for their time and attention.

The realization of this thesis was possible thanks to the funding of the Migration, Inequalities and Labor (MINLAB) doctoral training unit, granted by the National Research Fund of Luxembourg (FNR). The University of Luxembourg offered me an unvaluable opportunity and a great level of research infrastructure. I feel privileged and deeply grateful.

Finally, I am forever thankful to my family and friends for standing by me in these years. Grazie di cuore a Ersilia, Alessandra, Giuseppina, Carla e Sergio. In particular, my most sincere *merci* goes to my partner Gauthier Dero, who's been a greater support than I could ever had wished.

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Abstract

This dissertation consists of three chapters. Each chapter constitutes a self-contained study, tackling a salient subject within the economics of international migration.

◇ **Chapter 1: Ancestral Diversity and Performance: Evidence From Football Data.** Co-authored with Michel Beine (University of Luxembourg) and Skerdilajda Zanaj (University of Luxembourg).

The theoretical impact of diversity is ambiguous since it leads to costs and benefits at the collective level. In this paper, we assess empirically the connection between ancestral diversity and the performance of sport teams. Focusing on football (soccer), we built a novel dataset of national teams of European countries having participated in the European and the World Championships since 1970. Ancestral diversity of national teams is based augmenting the diversity index with genetic distance information on every players' origins in the team. Origins for each player are recovered using a matching algorithm based on family names. Performance is measured at both the unilateral and bilateral level. Identification of the causal link relies on an instrumental variable strategy based on past immigration at the country level about one generation before. Our findings indicate a positive causal link between ancestral diversity and teams' performance. We find that a one-standard increase in diversity leading to ranking changes of two to three positions after each stage of a championship.

◇ **Chapter 2: The Migration Crisis in the Local News: Evidence from the French-Italian Border.**

This paper investigates the impact of local exposure to the migrant crisis on the local news market. Exploiting a narrow geographical setting, it explores a policy dating from June 2015, whereby French authorities introduced militarized controls at the Italian frontier. With the border controls in place, groups of migrants and asylum seekers who had planned to cross the border irregularly were pushed back to the Italian lands. With rejected migrants clustering at the border, natives residing along the Italian region were unevenly exposed to their settlement. Taking advantage of this unequal treatment as a natural experiment, this study uses novel data collected on the text and on the number of local news items for the border areas of Liguria, Italy, between 2011 and 2019. It documents that the backlog of migrants

in the Italian border area was substantially mediatized: coverage of migration rose most in the most exposed municipalities. Conversely, anti-immigrant discourse in the news grew more in areas least directly in contact with the border. Exploring further this framing dimension, the bias effect turns out to be shaped by readers' demand and to be closely associated with local news penetration. Finally, this study documents that anti-immigrant slant and voting preferences share a similar direction, while a related broad pattern also appears in hate-crime records.

⋄ **Chapter 3: The International Drivers of Asylum Policy.** Co-authored with Melissa Tornari (University of Luxembourg).

In this paper we explore the role of international interactions in affecting asylum policies: i.e. how a country's policy implies a reaction of connected countries. We complement to the existing empirical literature by adopting a flexible Spatial Dynamic Panel Data model that allows to include both time and space autocorrelation in the policy measures, as well as space dependencies in the explanatory variables. Importantly, we separate out strong cross-sectional dependence stemming from heterogenous responses to unobserved common shocks. This step proves crucial for the identification of spatial effects. We exploit data on acceptance rates and a measure of speed in processing requests, for 23 European countries at quarterly frequency between 2013 and 2019. By relying on numerical observables, we avoid the issues of quantifying qualitative policy measures. Additionally, we allow spatial interactions across countries to take place along the geographic dimension, but also along linguistic proximity. Results show asylum policies are strategic substitutes, with key results featuring for both dimensions of interactions. Finally, we document spillover effects emerging from Germany's reception announcement in September 2015 on cross-country processing speed, as well as significant indirect effects resulting from the arrivals of migrants at the external EU borders.

Declaration of co-authorship

This section contains an overview on the role of the co-authors in the realization of this thesis.

◇ **Chapter 1: Ancestral Diversity and Performance: Evidence From Football Data.** Co-authored with Michel Beine (University of Luxembourg) and Skerdilajda Zanaj (University of Luxembourg).

Michel is at the origin of the research idea. I handled the data manipulation and estimation side, with a close guidance of the co-authors. All technical aspects of the paper were discussed and jointly decided by the three co-authors. I wrote a first draft that was then improved by a deep and careful editing of Skerdilajda and also attentively revised by Michel.

◇ **Chapter 2: The Migration Crisis in the Local News: Evidence from the French-Italian Border.** This study is a single-authored paper.

◇ **Chapter 3: The International Drivers of Asylum Policy.** Co-authored with Melissa Tornari (University of Luxembourg).

I was at the origin of the research idea. I handled the data manipulation and estimation side. All technical advancements of the paper were jointly agreed by the co-authors. I wrote an initial draft that was then carefully revisited and enriched by Melissa. Melissa also extended the review of the literature.

Introduction

During the *Age of Mass Migration* (Hatton & Williamson, 1998),[1] a substantial proportion of European population emigrated from Europe. Roughly 55 million reached the Americas and Australia as main destinations. Some decades later, starting from the aftermaths of World War II (WWII hereafter), migration patterns reversed and large-scale immigration to (and within) Europe became a more prominent phenomenon to reach what Glynn, 2021 termed *the Age of Global Immigration*.

Since the 1950s, the history of European migration saw several stages. North-Western Europe's economic boom after WWII spiked demand for manual labor up and led to the creation of several guest worker programs.[2] At the same time, a decolonization process took place for several colonial entities such as Belgium, France, Portugal, the Netherlands and the UK, leading to a substantial degree of intercontinental migration flows (De la Rica et al., 2015).

This panorama saw some further reshaping with the onset of the Oil Crisis of 1973. Due to the negative downturn of the economy, this period marked the enactment of measures by several European countries to halt guest work inflows. These measures indirectly led several guest workers to settle as permanent immigrants. As the economy receded, public attention on the topic of migration rose, and immigration concerns gained prevalence in the political debates of the receiving countries (Doomernik & Bruquetas-Callejo, 2016). In the 80s and 90s, changes at the level of immigrant composition took place due to several phenomena, i.e. the economic growth of Southern Europe, attracting returnees and new immigrants from Latino America and North Africa, the fall of Berlin Wall leading to westward movements and to a connected rise in asylum migration. East to west migration also followed from the Eastern EU integration in the 2000s, with overall figures somehow reduced by the outbreak of the 2008's financial crisis.

Finally, the 2010s marked an unprecedented rise in undocumented immigration to Europe. Following high levels of economic and political instability in several Near East and African countries, asylum applications in Europe skyrocketed to over 3 millions in the peaking years from 2014 to 2016. This set of events resulted into

[1] Spanning 1850-1914.

[2] Main receiving countries were Belgium, France, Germany, Luxembourg, the Netherlands, Sweden, and Switzerland, while main senders were Algeria, Greece, Italy, Morocco, Portugal, Spain, Tunisia, Turkey, and Yugoslavia, see Van Mol and de Valk, 2016 for more details.

a viral public attention (Chouliaraki et al., 2017) and constituted an urgent call for the revision of existing EU agreements on asylum reception. Despite a relative arrest in arrivals resulting from COVID-19 mobility restrictions, tensions across EU countries on the issue of asylum migration are still on the table in the most recent period. One example reflecting the rise of political extremism and tensions across national leaders is the emblematic statement of Hungary's prime minister Viktor Orban in late July 2022, who made his despise for "racial" mixing explicit, and caused a substantial backlash. To exemplify the migratory patterns discussed so far, Table 1 reports the evolution of net migration -i.e. the number of immigrants minus the number of emigrants- for European countries in some key moments over the last 70 years.

Within this setting, understanding the issues and opportunities behind the evolving landscape of migration patterns is a crucial step to take for informed policy making, in Europe and beyond. This dissertation finds its roots in this historical and demographic context. Specifically, it addresses empirically some key economic aspects emerging from migration in Europe in the last 50 years. Approaching these phenomena from different angles, the three chapters of the present thesis constitute three independent empirical studies.

The first chapter is a joint work with Michel Beine and Skerdilajda Zanaj. In this study, we explore whether and how diversity in the composition of groups affects group-level performance. Diversity here is defined as the likelihood of any two individuals in the same group to be of different ancestry. This research question has been the interest of at least two strands of literature. On one side, cultural economists have explored the role of ethnic diversity on several aspects of the economy (Ager & Brückner, 2013; Alesina et al., 2016; Ashraf & Galor, 2013; Docquier et al., 2019; Easterly & Levine, 1997), typically taking a macroeconomic perspective. How a diverse community jointly contributes to the economy is not unambiguous (Alesina & Ferrara, 2005). Within an aggregate production function, higher diversity in individual backgrounds potentially matches a greater diversity of the skill composition of labor. Then, if complementarities exist across these skills, production rises. On the other hand, perceived differences may lower cohesion and decrease willingness to cooperate, thus provoking inefficiencies, so that the net effect for economic productivity ultimately depends on the trade-off between these two mechanisms.

Despite the lack of an overall consensus on the role of diversity for economic performance, recent studies have marked the crucial role of polarization for the political salience of diversity (Esteban & Ray, 2011). On the other side, management studies have zoomed into global organizations as multicultural teams, were the same production function paradigm broadly applies, and have described specific aspects of how diversity interacts with the corporate structure (Earley & Mosakowski, 2000; Horwitz & Horwitz, 2007; Miller & del Carmen Triana, 2009; Shin et al., 2012).

In our work, we bridge between these two literatures and bring the research question to the context of professional sports (soccer in particular). Culturally and financially, soccer is a major business and a leading sport in the European landscape: €5.7 billion in revenue were reported in UEFA's financial statements of 2020/2021. This, combined with the richness of observable data, makes soccer a perfect laboratory to test the role of group diversity on performance.

We built a novel dataset of national teams of European countries having participated in the European and the World Championships since 1970. We depart from Ingersoll et al., 2017's approach as we enlarge the scope of the analysis to the quasi-totality of European countries and as we focus on national teams rather than clubs. By focusing on national athletes, we propose a novel instrumental variable to ensure causality in our results: we instrument the level of diversity of a national team with the diverse composition of migrants lagged one generation. Heterogeneity in the composition of citizens today results from different historical dyadic migration patterns, as discussed at the top of this introduction. As a consequence, this diversity will be reflected in the composition of national teams as well.

Crucially, we give importance to genetic distances between origins. Basic measures of diversity, such as the inverse Herfindahl-Hirschman Index (HHI), have been criticized[3] as they impose equal levels of proximity across each origin group, whilst diversity may be more or less salient depending how groups are (perceived to be) different between one another. Following the works of Arbatlı et al., 2020; Ashraf and Galor, 2013; Spolaore and Wacziarg, 2009, in our approach genetic distances serve as a proxy for perceived and actual differences across origins. Football performance is measured at both the unilateral (i.e. championship) and bilateral (i.e. match) level, and our findings indicate a robustly positive causal link between ancestral diversity and teams' performance. We find that a one-standard deviation increase in diversity leads to ranking changes of two to three positions after each stage of a championship. As migratory patterns in Europe are on the rise, understanding the potential benefit of diverse talent is key to boost acceptance in the public and combat the well-present scourge of racism and discrimination in European soccer.

Chapter 2 and Chapter 3 focus on asylum migration and investigate the migrants crisis period in Europe under two different lens.

Chapter 2 investigates how the presence of asylum migrants impacts the delivery of information around migration, with a focus on the local news market, and it documents how patterns in the news link with the local political economy. A rich literature in the political economy of migration has suggested that the presence of migrants is directly linked with anti-immigrant attitudes and populist voting (Campo et al., 2021; Edo et al., 2019; Otto & Steinhardt, 2014).

On the other side, media, and news more specifically, are powerful communication tools that shape and diffuse attitudes and preferences of individuals. This is documented for instance in the empirical works of Djourelova, 2020; Keita et al.,

[3] See for instance Greenberg, 1956.

2021 and more broadly by a set of recent contributions that benefitted from the current evolutions in text-mining and big-data treatment techniques (Gentzkow et al., 2019). Crucially though, the supply of information in the economy is not an exogenous phoenomenon. In most circumstances, news firms carefully consider readers' preferences for their production choice (Gentzkow & Shapiro, 2006).

In this study, I focus on the missing link between these sets of evidence. I investigate how the migrants-crisis shapes the content of news and how this interacts with supply versus demand for information by readers. Finally, I investigate how news content patterns match with patterns in the attitudes of natives towards migration. To do so, I exploit a localised geographical setting, and explore a specific policy enacted in June 2015. Starting from this period, French authorities introduced militarized controls at the Italian frontier. The aim of these controls was the tracking and push-back of irregular migrants attempting to cross the borders to reach the French territory.

Undocumented migration to Italy peaked to roughly 170 thousand in 2014. Among these arrivals, many attempted to bypass the Italian bureaucratic procedure to reach their intended destinations in other European countries, and transited through specific gateways at the Italian borders. France's border controls were established as a response to the growth in these transits. For morphological reasons, these events were particularly prominent in the coastal borders with the region of Liguria (Italy). Focusing on this Italian side, this study involves the construction of a novel dataset of local news distribution and content at municipality level for the period between 2011 and 2019. Whether natives were directly exposed to the presence of migrants depended on their proximity to the borders. Therefore, this study exploits commuting distance from the border as a continuous degree of treatment for the direct exposure of natives to the backlog of undocumented migrants, within a difference-in-difference specification.

Results show that the backlog of migrants in the Italian border area was mediatically important: coverage of migration in the local news rose most in the most directly exposed municipalities. At the same time, however, anti-immigrant discourse in the news is found to grow relatively more in the areas further away from the border controls. Digging into this framing dimension, evidence suggests that anti-immigrant discourse is boosted by sources with the highest demand, and that it goes hands in hands with a higher penetration of local news. Anti-immigrant discourse is therefore demand-driven. Finally, the study documents that such framing effect shares the same direction with voting preferences and hate-crime records, suggesting that what happens in the news also happens at the level of the local political economy.

These findings lead to at least three crucial implications. First, studies considering the persuasive power of media have to carefully address issues of reverse causality between demand and supply for information. Second, exposure of natives to migrants leads to worse reception, but more so when it is indirect and partial

(Allport, 1954; Steinmayr, 2021). Third, a strong attention by institutions is needed not only at the external EU borders, but also at the internal ones, especially in the context of a migration crisis, where international cooperation becomes trembling.

Chapter 3 is a study co-authored with Melissa Tornari. In this paper, we investigate the role of cross-countries interdependencies in explaining policy decisions on asylum reception. In the last couple of decades, European countries have been working on several agreements to promote the development of a common asylum system. Despite these efforts, anecdotal evidence suggests that the reception of asylum seekers in Europe is still far from reaching uniform standards. Examples of individual decision making come for example from the Danish efforts to deflect migrants from outside the EU to other destination countries (Agersnap et al., 2020), and to deter their migration intentions of potential asylum seekers at origin.[4]

In this paper, we investigate whether country decisions on the reception of migrants in the asylum crisis influence and are influenced by the choice of their most closely connected neighbors. As asylum seekers tended to undertake journeys that involved the crossing of several countries through specific routes, we focus on geographic proximity as a proxy to capture the directions of potential leakages and deflections of migrants induced by a policy change. Expecting these leakages, neighboring countries would then be more sensistive to the events occurring at their borders, than to those further away. We additionally consider linguistic proximity as an additional channel for these interactions. The linguistic channel may capture cultural as well as institutional similarities that are not fully correlated with the geographic dimension and may also signal a greater chance of exposure to cross-country information and likelihood of interaction. Specifically, we adopt a flexible dynamic spatial panel data model with interactive fixed effects, proposed by Shi and Lee, 2017. The presence of spatial correlation would signal that asylum responses of countries are not spatially random, i.e., that despite an overall common agreement, European states tend to cluster their policy decisions based on the decisions of related countries.

With the help of Shi and Lee, 2017's estimator, we separate the (possibly heterogenous) effects of unknown common factors, that lead to a strong cross-sectional dependence in the data. Strong cross-sectional dependence may interfere in the estimation of spatial effects, while the direction of this confounding is not *a priori* unambiguous. Our specification controls for the effect of time, and the estimator handles simultaneity issues.

We focus on measurable policy outcomes, namely acceptance rate and processing speed, in a similar vein to Bertoli et al., 2022. The existing literature on the role of cross-country interactions on migration and asylum policy tends to propose a variety of qualitative outcomes, which hinders interpretation and comparability across findings. Our framework proves convenient to estimate dynamic spillover

[4] https://www.bbc.com/news/world-europe-34173542

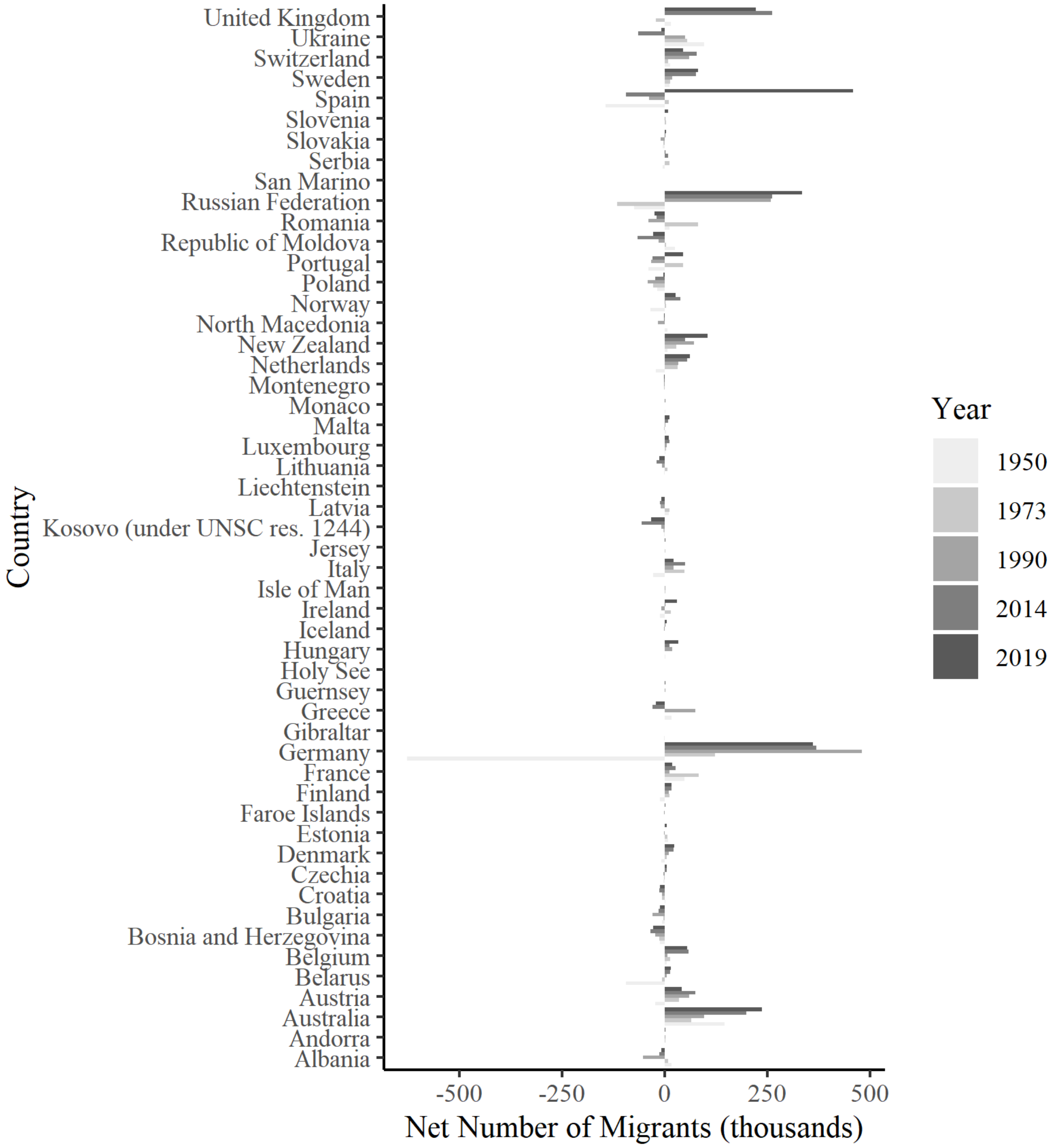
effects of explanatory variables of interest.

We focus on two in particular, i.e. i) the positive reception announcement introduced by Germany in 2015: we measure the diffusion effect, if any, exerted on the asylum policy making of other EU countries; ii) the effects of migrants arrivals at the main external gateway countries in Europe, following the migratory routes defined by the European Border and Coast Guard Agency (henceforth FRONTEX).

Our results show that considering strong cross-sectional dependence is key when exploring the role of spatial interactions. Spatial relations differ substantially in size and significance, once we have controlled for the heterogenous effects of common unknown factors. Our findings indicate countries interdependencies exist, and countries strategic substitutes in acceptance rates and processing speed -when a country becomes more open, others respond with tightening. This interdependence could rise if these countries fear leaking inflows, caused by a greater attraction of migrants towards the direction of the more favourable country (Görlach & Motz, 2021).

Additionally, we document that the arrival of migrants at the external EU borders decreases the acceptance rates in geographic neighbors, and increases their speed of processing applications. We see this as evidence that pressure at the borders leads to an indirect reaction of countries to minimize the costs of an elongated reception stage. Despite these considerations, we find that the declaration of Germany to open their doors to asylum requesters in September 2015 led to a relaxation of processing speeds of connected countries. This possibly indicates that with Germany taking a leading role, other countries respond by relaxing their processing efforts. While we do not claim full causality in our findings, we are able to identify the crucial role of interactive effects in spatial model applications, and highlight the importance of reaching cross-country agreements in handling the reception of asylum inflows.

Figure 1: Net migration in Europe, time comparisons.



Notes: This figure shows the evolution of net migration in Europe over time. The x-axis reports the level of net migration in thousands for each country in the y-axis. Different shades pertain to different years, as reported in the legend. A darker color represents a more recent period. Data source: United Nations, Department of Economic and Social Affairs, Population Division (2022). World Population Prospects 2022, Online Edition.

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Chapter 1

Ancestral Diversity and Performance: Evidence From Football Data

Abstract

The theoretical impact of diversity is ambiguous since it leads to costs and benefits at the collective level. In this paper, we assess empirically the connection between ancestral diversity and the performance of sport teams. Focusing on football (soccer), we built a novel dataset of national teams of European countries having participated in the European and the World Championships since 1970. Ancestral diversity of national teams is based augmenting the diversity index with genetic distance information on every players' origins in the team. Origins for each player are recovered using a matching algorithm based on family names. Performance is measured at both the unilateral and bilateral level. Identification of the causal link relies on an instrumental variable strategy based on past immigration at the country level about one generation before. Our findings indicate a positive causal link between ancestral diversity and teams' performance. We find that a one-standard increase in diversity leading to ranking changes of two to three positions after each stage of a championship.

1.1 Introduction

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

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

Ethnic indentity is a key dimension of diversity, exerting a potential effect on productivity and collective performance. Previous work on ethnic diversity suggests that higher diversity exerts a positive effect on global productivity (Alesina & Ferrara, 2005; Alesina et al., 2016). Regarding the inherited aspect of this dimension, Ashraf and Galor, 2013 focus on genetic diversity and argue that there is an optimal level in terms of productivity. On the one hand, diversity brings complementarity in skills, which results in a higher level of productivity. On the other hand, genetic distances across populations are proxies for differences in history, culture, and social values. These can be seen as an excellent summary statistic capturing divergence in the whole set of implicit beliefs, biases, conventions, and norms transmitted across generations—biologically and culturally—with high persistence (Spolaore and Wacziarg, 2009; 2016; 2018). Besides, ancestry affects culture even after several generations (Guiso et al., 2006) not only because culture is transmitted to an enormous degree intergenerationally, but also because differences among individuals with different ancestries are related to differences in their values and preferences (Bisin & Verdier, 2001). These divergences associated with diversity might mitigate or offset diversity's positive impact on productivity.

In this paper, we investigate the role of ancestral diversity in the performances of national football teams. One interesting aspect of this sports activity is the fact that performances are measured precisely and are much less subject to measurement errors compared to other economic activities. The case of football is interesting, beyond the fact that it is the most popular sport worldwide, since the performance of a team relies on the interaction of players who need to have very different skills, depending on their position on the pitch. This clearly refers to the complementarity of skills channel mentioned above. It is empirically unclear in football to what extent the cultural channel and the divergence-in-beliefs channel associated with higher diversity are substantial and might offset the positive effect of the skill complementarity. Anecdotal evidence suggests, however, that there is some belief that diversity does affect football performance positively. In 2012, Belgium succeeded to a 2–0 away win over Scotland during the World Cup qualification process. Commenting on this result, Scotland assistant manager Mark McGhee described the Belgian team's skill pool as follows: [5]

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

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

> [diversity] delivers practical benefits since it ensures that a society can draw upon the energy and skills of all... people. And if you doubt that, just ask the French football team that just won the World Cup because not all these folks look like Gauls to me....[6]

As of February 18, 2021, Belgium and France were ranked first and second worldwide respectively, according to the World Rankings provided by the Fédération Internationale de Football Association (henceforth FIFA).[7] One of the goals of this paper is to check whether these perceptions are supported by some sound statistical analysis.

To establish a causal link between the sportive teams' ancestral diversity and performance, we develop specific measures of the key dimensions, i.e., performances and ancestral diversity of football teams. Performance data are collected at the match and tournament level for European teams based on their results at the World Cup and the European championship competitions from 1970 onward. At the

[5] Mark Wilson, "Brilliant Belgians just incomparable insists Scotland assistant coach McGhee,"

[6] France24, "In Mandela address, Obama cites French World Cup model as champs of diversity,"

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

tournament level, our benchmark performance indicator is the Elo score ranking of the national team that gives a synthetic value of the recent performances of any national team. At the match level, we use the goal difference as the benchmark but show that our results are robust to alternative measures. The ancestral diversity of each team is based on the bilateral genetic *distance* between players. Data on genetic distance comes from Spolaore and Wacziarg (2009), who using data from Cavalli-Sforza et al., 1994, quantify a genetic distance that effectively measures the time since two populations shared a common ancestor. We interpret this index of genetic distances to capture long-term population relatedness in line with the argument by Dickens, 2018 that connects genetic distances to the complementarities of people dissimilarities. On the one hand, narrow genetic distances mean similar traits and ideas, and thus easier communication but fewer novel ideas to share among similar populations. On the other, more significant genetic distances imply a long history of remoteness and a broader spectrum of non-overlapping but more likely novel and complementary ideas and traits to share. We follow the approach of using family names to capture the ethnic background of individuals adopted in different fields such as the patents literature (Kerr & Kerr, 2018) or the study of intergenerational mobility (Clark, 2015).[8] Our measure of ancestral diversity at the national level suggests that diversity has changed significantly over the period of investigation, especially in countries of past intensive immigration.

The econometric analysis of the causal link between ancestral diversity and performance of national teams is likely to be affected by a set of confounding factors that can bias the estimated impact of diversity. Our identification strategy relies on an instrumental variable (IV) approach that makes use of the ancestral diversity of past immigration flows at the population level. More specifically, we instrument the ancestral diversity of football's national teams with a measure of ancestral diversity for the immigration stocks about one generation before (20 years). The idea is that higher diversity in immigration yesterday increases the diversity of second-generation migrants who can today play for the national team of their parents' adopted country. The strict rules of eligibility for participation on a national team in football prevent the implementation of a strategy in which diversity could be manipulated by national federations. This lowers the concern that this instrument does not comply with the exclusion restriction. Our IV results therefore allow to uncover an overlooked benefit of immigration, namely, its long-run benefit in terms of performance in collective sports.

We hypothesize, and then show empirically, that ancestral diversity implies signi-

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

ficant complementarities (tactical, technical and physical) among players, affecting performance positively. It is important to note that we do not, of course, address the direct effect of genes on sports performance. In contrast, our analysis addresses the benefits and drawbacks of ancestral diversity on performance measured at a collective level. We expect ancestral diversity in sports to affect performance through a variety of channels. These channels include (i) the ability to play as a team, conveyed by norms of cooperation belonging to different nationalities; (ii) the creativity of novel ways to play sports; and (iii) the improved complementarities among players in view of the different skills required for different roles in the game.

We find a positive net benefit on team's performance. Our results hold at both the tournament and match levels. At the tournament level, along with our measure based on the Elo scores, a one-standard-deviation increase in diversity would lead to a scaling upward of about 2 to 3 positions after each tournament. At the match level, a one-standard-deviation increase in diversity yields an increase of one point in the goal difference. These findings are robust to a set of robustness checks and to some invalidation exercises. The results are also robust to whether passive players are included or not, to alternative measures of ethnic distance, to the way bilateral performances are captured, and to the fact that hosting teams usually have an advantage in football. In addition, we control for coaching quality that could confound the identification of the causal impact of diversity. The results are also robust to the number of years that past immigration flows are expected to impact ancestral diversity of national teams in the first stage of the IV analysis. Finally, we perform a placebo test using performances in athletics, i.e., a sport in which diversity should not play any role, given that competitions do not involve any collective effort. We do not find any role of ancestral diversity in explaining performances in athletics.

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

The paper is organized as follows. Section 1.2 briefly reviews the relevant literature. In Section 1.3, we describe the data used in our analysis. Section 1.4 introduces the empirical analysis. Section 1.5 presents the main results, discusses identification issues, and Section 1.6 exposes the robustness checks. Our placebo analysis is detailed in Section 1.7. Section 1.8 concludes.

1.2 Literature review

The economic implications of diversity have produced a very extensive literature. Prior studies investigate the effects of ethnic diversity on growth (Ager & Brückner, 2013; Docquier et al., 2019; Easterly & Levine, 1997), on economic prosperity (Alesina et al., 2016), on trade (Alesina et al., 2000), on polarization (Bove & Elia, 2017), on individuals' preferences (Alesina & Ferrara, 2005), on community participation (Alesina & La Ferrara, 2000) and on the provision of public goods (Spolaore & Wacziarg, 2009). Prior studies also relate diversity to the performance of collective organizations. The seminal model of Lazear, 1999 emphasize the role global organizations as multicultural teams. To offset the costs of cross-cultural interaction, the complementarities among different workers must, however, be substantial. Delis et al., 2017 use a panel of U.K. and U.S. firms listed on the stock market and track the ancestral diversity of the board of directors, finding positive effects on the firm's performance as measured by risk-adjusted returns and the Tobin's Q. Delis et al., 2021 apply a similar analysis to the movie industry, finding an optimal degree of ancestral diversity of actors and directors on the box office figures of attendance. In Prat, 2002, diversity of team members results in diverse decision-making processes, which brings benefits in the case of actions' submodularity. Studying working groups in a multinational firm setting, Earley and Mosakowski, 2000 propose and document that teams effectiveness is highest at the bottom and top levels of group heterogeneity, whilst Dumas et al., 2013 document that demographically dissimilar groups tend to respond less well to corporate activities that aim at stimulating group cohesion. Focusing on the mechanisms, Miller and del Carmen Triana, 2009 identify innovation and reputation as important channels in the role of racial diversity of board-directors and corporate performance. Shin et al., 2012 analyze the individual-level outcomes of team diversity in the context of Chinese firms. They find that a positive link between cognitive diversity and creativity depends on individuals' beliefs on their own creativity, and highlight the key role of leadership in shaping a positive effect. In the findings of Watson et al., 1993 and Horwitz and Horwitz, 2007, performance gains from diverse teams would materialize, after allowing for some initial burning phase in the team formation.[9]

The literature that stresses on the long-term dimension of population diversity is more recent. Spolaore and Wacziarg, 2018, Ashraf and Galor, 2013 and Delis et al., 2017 are seminal contributions that relate genetic diversity and performance. Distinguishing between the measurements of diversity is relevant because these may present different patterns (Alesina et al., 2016). To the best of our knowledge, our paper is the first study to explore the effects of ancestral diversity on sports

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

performance.

Focusing on sports, Kahane et al., 2013 provide evidence from hockey and generally find a positive effect of cultural diversity. Parshakov et al., 2018 use e-sport data to investigate the impact of cultural, language, and experience heterogeneity on performance. Cultural diversity correlates positively with tournaments performance, while language and experience diversity are found to affect performance negatively. Gould and Winter, 2009 build a panel of baseball players from 1970 to 2003 and observe that workers' (players') efforts and interactions depend on the complementarities in the production technology. A recent contribution by Tovar, 2020 explores the link among diversity, national identity, and performance at the player and team level, analyzing data from the Spanish and English leagues. The study found a non-linear relationship between the team's and the players' performance.[10] Also concentrating on club-level performance, Brox and Krieger, 2019 provide evidence from German men's football, finding that an intermediate level of birthplace diversity maximizes team performance. Ingersoll et al., 2017 enlarge the set of countries and investigate the effect of cultural diversity on the club teams' performances in the top leagues in the UEFA Champions League (2003–2012) for Germany, England, Italy, France, and Spain. In their findings, culturally heterogeneous teams outperform homogeneous ones, cultural diversity being proxied by linguistic diversity data based on players' nationality.

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

1.3 Data

To analyze the impact of ancestral diversity on the performance of national football teams, we collect and build indicators of diversity and performance as well as other variables. We start by explaining how key data are built, namely, ancestral diversity at the team level and the performance. We then present other variables that enter

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

into the subsequent econometric analysis.

1.3.1 Measuring ancestral diversity at the team level

Our key indicator of interest to explain the performance of a given national football team is its ancestral diversity. To capture this relationship, we gather information on the team composition. From this, we then establish a measure for the characteristics of each team member and relate how the individual information on the player's origins is combined to yield an indicator of diversity.

National team composition.

We collect data on the composition of national squads from the website *world-football.net*, with some comparisons and checks using *soccerway.com* and Wikipedia. Squad data on Turkey was absent for two periods in the main source, and the desired information was obtained through the source *https://www.national-football-teams.com*. For every European team that entered either tournament $\in$ {Euros, World Cup} over the period 1970 to 2018, we obtained information on players' names, their age, and their minutes/appearances in the competition at each stage $\in$ {Qualification, Finals}.[11]

In our baseline specifications, we include each player from the squad list in our diversity measure, regardless of his appearance time. Ingersoll et al., 2017 focus on football clubs and identify that cultural diversity on the pitch matters positively for performance. Yet they find an insignificant effect for off-the-pitch interactions. To accommodate this possible heterogeneity, we also include minutes played as weights in our diversity calculations in one of our sensitivity checks.

Ethnicity of players.

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

More specifically, for each unique surname in the full list of players in our dataset,

[11] Given the full name lists, we proceeded with a splitting to separate the father name information. The web source *soccerway.com* presents players' profiles with names and surnames separated. Whenever we could match the player in our sample to his profile on *soccerway.com*, we used the surname as presented in the source. In the other occurrences, name splitting was performed according the following decision rule: we extracted the last part of the full name instance by taking into account particular nominal particles, such as "De," "Van," "Van Der," "Von," "Di," etc. With Spanish and Portuguese teams, the splitting followed the typical country's customs: for Spain, the first surname corresponds to the father's surname, and vice versa for Portugal. We focus on father surnames for cross-country comparability.

this source provides the three countries ($country_1$, $country_2$, $country_3$) displaying the highest incidences (i.e., number of people having that surname in a particular country) and the highest frequencies (i.e., percentage of people having that surname in a particular country) of that specific surname. We then identify the best predicted country $i*$ for a surname as the country i associated with the highest value of the variable ($Incidence_i * frequency_i$, $i \in country_1, country_2, country_3$). This procedure avoids favoring very small countries, which would occur if we looked only at the frequency (e.g., virtually every surname in Monaco has very high frequencies). Further, it avoids favoring very big countries, as would happen if one relied on the incidence only (e.g., countries like the U.S. have generally higher incidences, even for rare surnames).[12] Our website of choice has the important feature of delivering accent-sensitive information, which increases precision when mapping a surname and a country of origin.[13] While measurement error concerns do arise with the choice of this proxy, this method performs quite well in capturing the second-generation of migrants who may still contribute to the team's diversity (e.g., French national Zinedine Zidane was born in Marseille and is of Algerian descent).[14] Examples of the prediction results are found in Appendix 1.B.[15]

Ancestral diversity.

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

[12] A further manual cleaning was performed using a language detection algorithm in Python. While these algorithms tend to perform best for common nouns rather than surnames and for phrases rather than single words, we compared the language predicted with the country predicted and assessed and eventually corrected a minority of surnames manually.

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

[14] As a further cleaning process, we used language-predictive libraries (TextBlob, langdetect) in Python to see whether the surname prediction coming from our algorithm was in line with these library-based predictions. With this approach, in some minor cases, we corrected a minority of surnames manually. cases, we corrected a small number of surnames manually. We clarify that the main purpose of this set of libraries is to classify sentences and common names, rather than family names. Further, they predict languages, rather than ethnicity. Further, they predict language rather than ethnicity. We therefore employed this tool very conservatively.

[15] Referring to the Belgium example in Appendix 1.B, it is obvious that the matching algorithm is efficient but not perfect. The match between the ethnicity and the surname is rather good (85 per cent of correct predictions). Two types of errors in terms of their incidence occur. The most detrimental error is the case of the striker Batshuayi that is spuriously attributed to the Belgian ethnicity (rather than to the Democratic Republic of the Congo). This error is due to the fact that this surname is rare and/or the coverage of surnames incidence in the DRC is rather poor. Most of the other errors have little if no impact on the diversity level. The reason is that surnames have either some French or Dutch connotations. This leads to spurious predictions in the case of Courtois, Lambert, and Meunier on the French side and in the case of Van Der Linden or Thissen in the Dutch case. Nevertheless, when attributed to an ethnicity of a neighboring country, there is no impact on the diversity measure since the genetic distance between Belgium and these countries is zero. The errors outlined in the Belgian case are also due to the particular linguistic situation of the country that has official languages (French, Dutch, and German) that originate in the neighboring countries.

$$Div_{ist} = \frac{1}{S_t} \sum_{j=1}^{N_t} \sum_{k=1}^{N_t} (p_{jt} p_{kt} d_{jk}), \; j \neq k \tag{1.1}$$

where p_{jt} and p_{kt} are the shares of players on the team (predicted to be from origin j and k respectively) belonging to the set of origins {1,...N_t} in team i for stage s of championship t. The fraction $\frac{1}{S_t}$ operates as a normalization factor for different squad sizes reported on the web source for the qualification stages. d_{jk} is the genetic distance between origin j and origin k, belonging to the set of surname-predicted origins in the squad. We use genetic distances in a fashion similar to Alesina et al., 2016, implying that our indicator can be seen as a weighted average of genetic distances over all origin pairs in the team. Data on bilateral genetic distance d_{jk} come from Spolaore and Wacziarg, 2009 who adapt distance matrices from the genetic literature (Cavalli-Sforza et al., 1994). Spolaore and Wacziarg, 2009 quantify a genetic distance - a molecular clock - that measures the time since two populations shared a common ancestor. In a similar vein as Dickens (2018), we interpret this index of populations relatedness as ancestral diversity. Players originating from populations with a narrow genetic distance have a high likelihood of similar traits and ideas, and thus they may possess fewer novel ideas and attributes to share. However, players from population groups with significant genetic distances have a higher chance of holding a broader spectrum of non-overlapping and more complementary ideas and traits. This approach is comparable to Ingersoll et al., 2017's linguistic diversity and does not profoundly differ from linguistic diversity indicators proposed by the seminal work of Greenberg, 1956 and re-elaborated in Fearon, 2003. The explicit consideration of genetic distances, key to our framework, allows more weight to be given to more genetically distant origins.[16]

As a snapshot example, we report in Figure 1.1 the cross-country variation of diversity in the EUROs 2016. A general pattern appears with Eastern Europe teams presenting lower diversity levels, whereas in Western Europe teams show higher levels of diversity, likely reflecting accumulated migration inflows over the recent decades.[17]

1.3.2 Measuring performances of national teams

We use two different dimensions to characterize the performances of national football teams. First, we use an absolute measure of performance of team i based on its ranking. This refers to the unilateral dimension of the performance data. Second, as a relative measure of performance, we use results at the match level. This measure is dyadic in nature, as the performance also depends on the performance of the

[16] This source led us to exclude two national teams from our sample, Andorra and Liechtenstein, as they are not part of the Spolaore and Wacziarg's dataset. All other countries were included.

[17] Kazakhstan's exception likely reflects the high ethnic diversity of the country: https://www.britannica.com/place/Kazakhstan/People

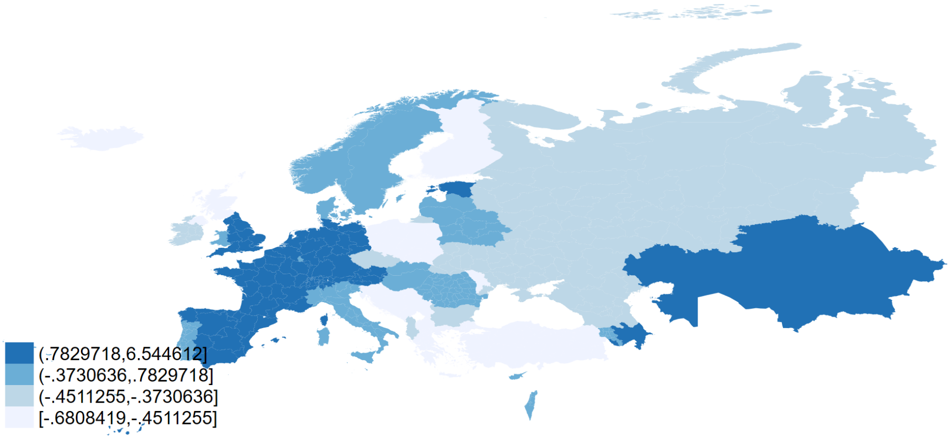

Figure 1.1: Diversity of national teams, EURO 2016, qualifications
Notes: In Figure 1.1, we plot a cross-sectional example for our diversity index, taking the 2016 EURO qualifications as the tournament of reference. As a general pattern, we observe higher levels of diversity in the Western area.

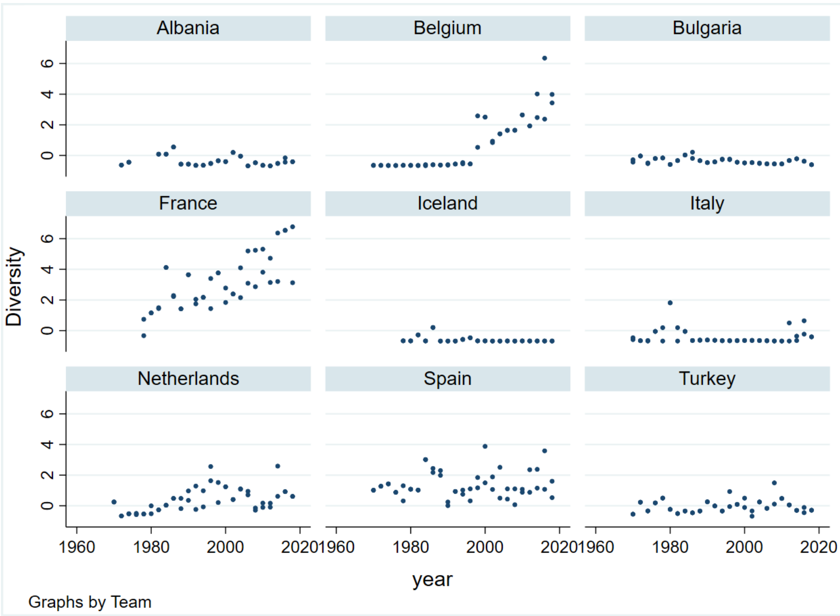

Figure 1.2: Ancestral diversity over time, selected national teams
Notes: In Figure 1.2, we present the time variation of our index of ancestral diversity for a subset of teams. While for some countries, like Belgium, we can identify a sudden change in the compositional diversity in the most recent decades, some other countries like France and the Netherlands display a smoother evolution pattern. This contrast might be explained by the different patterns of past immigration. Countries such as Portugal show higher, yet noisier team diversity levels. Italy, Albania, and Bulgaria are examples of countries with lower and relatively stable index values. These countries are, at least up to a recent period, mainly emigration rather than immigration countries. Iceland is a typical example with almost no ancestral diversity in its national team due to the relative isolation of the country in terms of human mobility.

opponent j.

In the unilateral setting, our performance indicator is the Elo score of a team.[18]

[18] Named after its inventor Arpad Elo, the Elo system was first introduced for comparing chess players' relative performances and was brought to football by Bob Runyan in 1997 (Langville & Meyer, 2012).

Updated after each game, the Elo score of a team is a function of its previous score, the realized and the expected results (given the opponent's relative strength) and the importance of the tournament. A complete description and formula are found in Appendix 1.A. Based on match-level information, we construct Elo ratings relative to the results of the EURO and World Cup qualifications and final stages for our whole sample. Our preferred measure would be the change in the score from the beginning to the end of the championship stage. For team i, performing in stage s, at Championship t, our baseline performance measure for the unilateral setting is therefore

$$Performance_{ist} = Elo\ score_{End,ist} - Elo\ score_{Beginning,ist} \tag{1.2}$$

The Elo score measurement is based on an updating process, where a new value at each match replaces the old value, according to the match result and its expectation. If a team is new in the sample, this computation requires an initial value. To provide reasonable starting values, we calibrate these instances with Elo score data available for every championship and stage at *eloratings.net*. As part of our battery of robustness checks, we also employ the Elo measures proposed on the website. Our computed outcomes differ from the website's in that *eloratings.net* includes all matches with all opponents (including those non-European Teams in the World Cup final stage).[19]

We show in Figure 1.3 a snapshot of the score change, taking the example of the 2016 EURO Championship qualification stage. As a benchmark, France (the tournament host) had a score change of zero. In 2016, countries like Iceland and Albania qualified for the final stage for the first time in the event's history. As Figure 1.3 shows, the Elo score updates give more weight to unexpected results. The worst performers in terms of score changes were the 2004 champion Greece and World Cup 2014 third-place finisher The Netherlands. The two teams did not qualify for the final stage. To complement with a time series example, Figure 1.4 plots the score change. The change in the score follows a stationary process, which rules out concerns related to the presence of unit roots in the outcome variables.

In the bilateral specification, the performance indicator is the goal difference. Data at the match level come from the collection *International Football Results from 1872 to 2020* assembled by Mart Jürisoo. It includes a complete and updated men's football international matches dataset.[20]

Figure 1.5 provides a summary of the key components of the bilateral measure, i.e., scored and received goals, broken down between home (left panel) and away (right panel) matches. The figures confirm that, on average, teams perform better at home than abroad, a well-known feature in football competitions. We will account

[19] It is worth mentioning that our Elo scores have a raw correlation of 97.5% with the website eloratings.net's index. In terms of the score change, the statistic is slightly lower (81.7%) but still very high.

[20] Mart Jürisoo, International Football Results from 1872 to 2020. Retrieved on January 2020. https://www.kaggle.com/martj42/international-football-results-from-1872-to-2017/tasks (version 4).

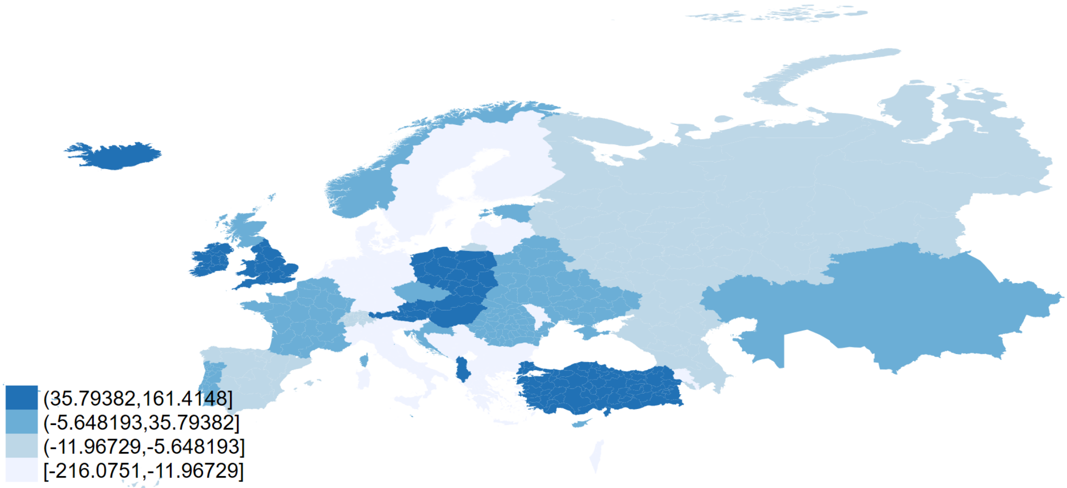

Figure 1.3: Change in Elo ratings of national teams, EURO 2016, qualifications
Notes: In Figure 1.3, we plot the cross-sectional example for our performance measure for the unilateral specifications, taking the 2016 EURO qualifications as the tournament of reference. The variation reflects the relative performances of teams that improved on or worsened their Elo scores, based on their expected vs. realized match results. (The details are in Appendix 1.A). As France was the host, the team accessed the final stage directly, therefore having a score change of zero.

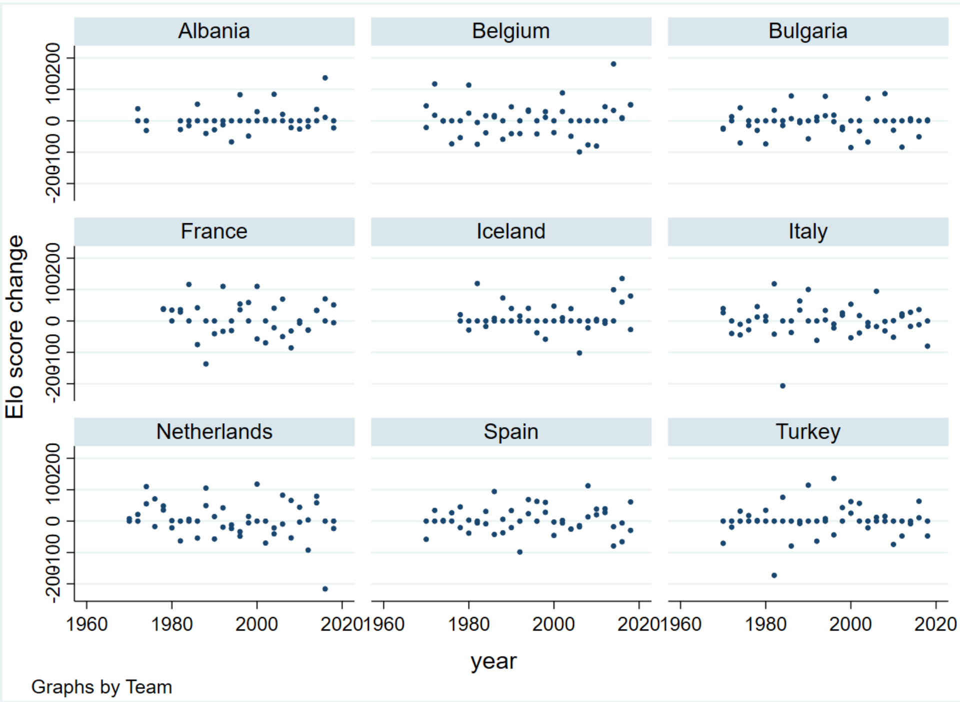

Figure 1.4: Elo score changes over time, selected teams
Notes: In Figure 1.4, we present the time variation of our Elo score change measure for a subset of teams. This picture reflects the stationary nature of the score.

for this feature in the econometric specification involving the bilateral dimension of performances.

Tables 1.1 and 1.2 in the Section 8 provide summary statistics for the main variables in the unilateral and bilateral data. The full list of countries included in the sample is given in Table 1.F.1.

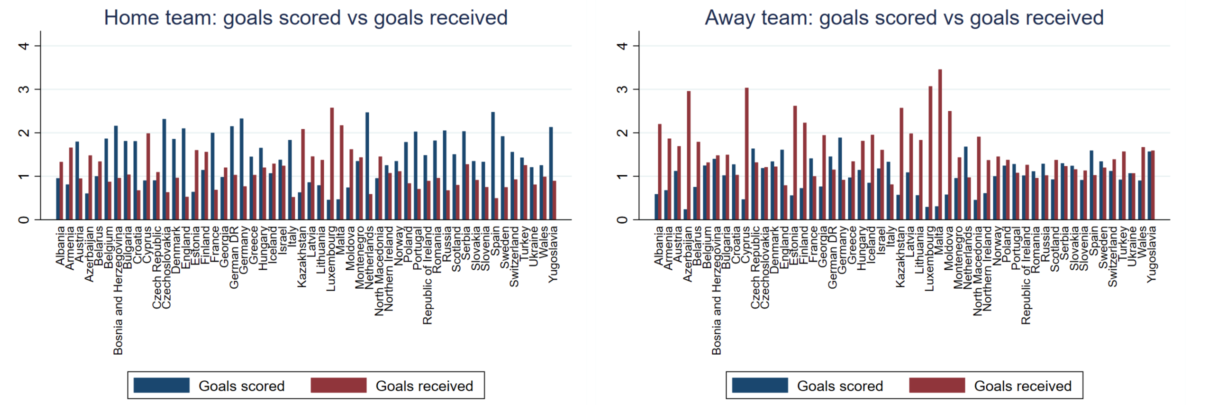

Figure 1.5: All-time goals scored and received, all national teams
Notes: In Figure 1.5, we present the all-time averages for the teams' bilateral performances, key outcome in our baseline estimations. Blue bars represent the average goals scored, whereas red bars represent the average goals received. On the left we list results for the teams listed as *home teams* in our dataset; on the right, we depict the same statistics for the teams when listed as *away teams*.

1.3.3 Other variables

We include various covariates affecting the performances of national teams. These variables are observed at either the team or country level. In our benchmark estimates, at the team level, we include the average age in its quadratic form and the players' appearance time variation for the team. We also include the standard deviation in the team members' minutes to better disentangle possible turnover decisions or other strategic concerns that may reflect the distribution of talent within the team. Country-level controls involve population (in millions), (the log of) GDP per capita, and past immigration stocks. Population data are retrieved from the Centre d'Études Prospectives et d'Informations Internationales (CEPII) for the period up to 2014 and then completed using World Bank data for the most recent values. GDP data (at constant 2015 prices) are extracted from the United Nations data office;[21] immigrant stocks are retrieved from the World Bank and start in 1960. As we lag this information, estimates that include this covariate will reduce the sample size to more recent years (beginning in 1978). We provide extensive information on all variables in our regressions in Appendix 1.F.

1.3.4 Instrument

Our goal is to estimate a causal relationship between the football teams' ancestral diversity and their performance. As we include a set of controls at team and national levels, together with team level fixed effects and country dummies, concerns regarding the endogeneity of our variable of interest are mitigated. Still, it is possible that a set of current political, cultural, economic or institutional conditions that are not considered in our framework will fall into the error term, resulting in a potential

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

omitted variable bias. As an example, naturalized players and, more generally, players who possess more than one nationality may be able to choose which national team to play for. They may have incentives to play for countries offering favorable conditions. These conditions may reflect financial, cultural, institutional and/or football-related resources that may correlate as well with the team performance. The squad selection process may also reflect cultural and/or institutional characteristics of the countries. If this selection is carried out to favor native players over second-generation migrants, this could cause inefficiencies in the talent selection, thus undermining the teams' performance. While part of these issues may be fixed over time, we allow for time variation in these characteristics and carry out an instrumental variable approach to ensure causality under these circumstances.[22] We use the level of ancestral diversity of past immigration of the country as an instrument. In the structural equation, we account for the size of past immigration as well as for the contemporaneous level of gdp per capita. The introduction of these controls mitigate the concerns of a direct impact of our instrument on the performance of the national soccer team through the potential beneficial economic effects of past immigration.

In order to play for national teams, players need to comply with strict conditions of eligibility and, in particular, need to be nationals of the represented country.[23] Eligible players would therefore be either naturalized immigrants, or children of natives or second-/third-generation immigrants in their adopted country.[24] National teams' diversity is therefore driven by the immigration history of the previous generation of their representing country. Countries with low immigration rates will therefore exhibit, everything else being equal, in a low diversity, transmitted over time within the same native population. This would also be true in countries with high immigration rates but with a concentrated origin of the immigrants. High diversity will be in countries with significant immigrant flows originating from diverse areas. As past immigration to a destination country translates into the heterogeneity in its nationals, we build a historical measure of country diversity that should predict how diverse the national team will be years later.[25]

To construct our instrument, we use data on the ethnic composition of countries

[22] It should also be noted that we build our diversity measure from ancestry information as proxied by surnames, which we argue captures the ancestral diversity well. We believe it is a suitable alternative to indices built on the country of birth or nationality. However, our diversity formula is a quantization process that involves measurement error concerns from at least two sources: our surname-to-country prediction, and the corresponding genetic distance measures obtained from the Spolaore and Wacziarg, 2009 dataset. We also rely on an IV strategy to account for this type of the endogeneity concerns.

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

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

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

provided by the University of Illinois Cline Center for Advanced Social Research. The Composition of Religious and Ethnic Groups (CREG)[26] is a time-varying measure that involves country-specific information on 165 large countries. In the sample, ethnic groups are given narrow definitions (e.g. *Russian*, *Romanian*, *Scottish*), which we converted to a reference country. The classification "others" is used by the data provider to group information on one or more unknown ethnic minorities.

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

$$IV_{it} = \sum_{j=1}^{N_{t-18}} \sum_{k=1}^{N_{t-18}} (p_{jt-18} p_{kt-18} d_{jk}), \ j \neq k \tag{1.3}$$

where p_{jt-18} and p_{kt-18} are shares of origins j and k immigration stocks, belonging to the set origins in country i at time $t-18$. The instrument is used for the qualification of the final phase.

As a decision rule, the group "others" in country i was assigned a median distant country j from the Spolaore and Wacziarg, 2009 dominant groups distance measure. The resulting variable was lagged to account for second-generation migration effects. While the lag choice is somewhat arbitrary, a higher lag would increase the data loss. For this reason, we use in our benchmark analysis an 18-year lag to limit the reduction in the final sample size, but 20-year and 22-year lags are also considered for sensitivity checking (see Section 6 below).

An inconvenience of the CREG dataset is that there are no data for a set of small countries (Kosovo, Malta, San Marino, Luxembourg, Montenegro, Faroe Islands), plus France and Iceland. To account for this issue, we complement the data with the World Bank's Global Bilateral Migration Database. For the years 1960-2000, this data source aggregates census and population register records, providing information at 10-year intervals. We interpolate these measures linearly for the missing countries to obtain two-yearly complementary information on our instrument. The resulting distributions are presented in the right panel of Figure 1.6 and are compared with the team diversity measure (left panel). The overall picture suggests a general increase in countries' ethnic diversity over time in the European continent (as displayed in the growing average values). However, this growth has been uneven across countries (as shown by the longer right tails). Although we formally assess the relevance of our instrument in the following sections, the patterns in the plots of Figure 1.6 seem broadly similar in the national teams' diversity and the diversity of the whole population.

[26] Cline Center for Advanced Social Research.

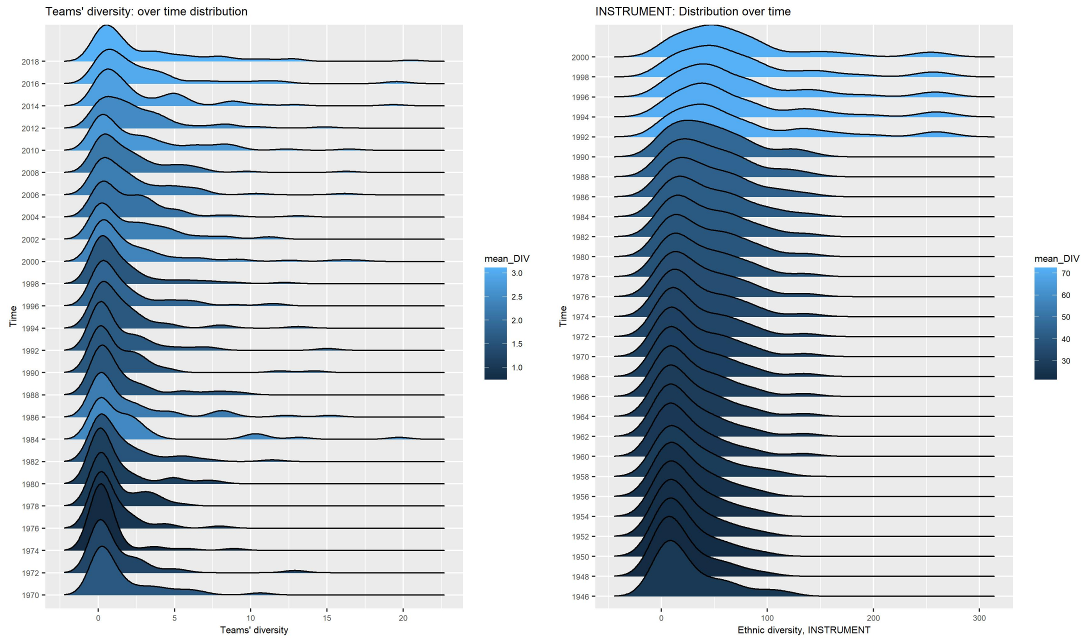

Figure 1.6: IV diversity over time

Notes: In Figure 1.6, we present the evolution of the distribution of diversity over time for our diversity index (on the left) and our IV index (on the right). Lighter colors represent higher yearly averages. This picture points to a positive evolution of national teams' diversity that is matched visually with a positive evolution in the lagged mean national diversity of our baseline instrument. This pattern is broadly in line with van Campenhout et al., 2019 who also suggest a growing trend in diversity occurring over time for the World Cup teams as a result of the countries' migratory histories and citizenship regimes.

1.4 Empirical analysis

We first carry out OLS estimations applied to the unilateral and bilateral settings in order to obtain the association between diversity and football performances. Since the estimations in these naive OLS regressions are likely to be biased by some confounding factors, we then move to the instrumental variable estimations to uncover a causal link between diversity and sports performance.

1.4.1 Benchmark estimations

Our benchmark unilateral estimation is as follows:

$$Performance_{ist} = \alpha + \alpha_s + \alpha_i + \alpha_t + \beta Div_{ist} + X'_{it}\Gamma + \epsilon_{ist} \tag{1.4}$$

where national team i performs in either or both stages s ={qualification, finals} of the two types of international tournaments, i.e., the FIFA World Cup and the UEFA Euro Cup in t $\in$ {1970, 1972, 1974, ...2016, 2018}.[27] We include stage, time, and team dummies $\alpha_s, \alpha_t, \alpha_i$ in all our specifications. Our regressor of interest is the level of ancestral diversity Div_{ist}, computed as detailed in Equation (1.1). Vector

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

X_{it}' includes the set of controls as explained in the previous section.

A non-negligible issue is that teams do not play the same number of matches and competitions due to the selection of teams participating in the final rounds. This is due to the specificity of the selection process of each competition for the final stage. First, by definition, teams not qualifying for the final round play a lower number of matches and competition. Second, some teams are or were automatically selected for the final stage. The host(s) of a tournament have always been exempted from the qualification stage in both types of competitions. Furthermore, up to a recent period, the title holder was also exempted from the qualification stage in the World Cup competitions.[28] In the first case, this out-selection process is directly linked with performance. To overcome such out-selection issues, our sample comprises the final scores of teams in both stages, whether they played or not in that stage. It follows that, if the team did not qualify for the next step or was the host of the competition, their scores will stay unchanged in those instances.

While fixed effects capture the effect of unobserved factors that are either constant over time or across countries, the set of covariates X_{it} arguably accounts for other unobserved factors. For instance, a country's financial resources may positively correlate with its national team's performance. At the same time, these resources may have acted as a pull effect for immigration, which would result in a higher level of diversity. We therefore include the log of GDP per capita and lagged immigration in our controls.[29] The demographic size of a country is in our controls as well, as it could also be linked to its diversity and the probability of having talented eligible players in every cohort.

In a separate specification, we allow for the inclusion of two further controls reconstructed from the match-level information, namely, the average diversity level and the average strength of the opponents. These two indicators permit us to better identify the effect of interest. First, we test whether the diversity of the adversaries was detrimental to the players' performance at the end of the championship. Second, we define the adversary's strength as the starting Elo score levels of the adversaries' pool, averaged across components. As the Elo scores capture the adversary's strength, a loss against a stronger team will be mitigated compared with a loss against a weaker opponent. While, for the sake of the competition, facing a more robust team may increase the chance of being eliminated, it also, in terms of score changes, is an opportunity to update the Elo score positively. These controls therefore allow a better establishment of the competition hierarchy by accounting for the variation in the Elo score due to a stronger opposition.

[28] Before the 2006 competition in Germany, the title-holding country was exempted from the qualification stage. In the European championship, the title holder has always been required to play the qualification games.

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

In the bilateral framework, we adopt the following specification:

$$Performance_{ijst} = \alpha_i + \alpha_j + \alpha_s + \alpha_t + \beta(Diversity_{ist} - Diversity_{jst}) + X'_{ijst}\Gamma + \epsilon_{ijst} \quad (1.5)$$

where the baseline performance indicator is the goal difference between team i and team j facing one another at stage s of championship t.

1.5 Results

1.5.1 Unilateral estimations

The baseline findings from the unilateral specification are reported in Table 1.3. The dependent variable for this set of outcomes is the Elo score change from the beginning to the end of the championship stage. Columns (1) to (4) gradually include covariates and reproduce panel model results without considering possible endogeneity concerns. Columns (5) to (8) show the IV results, where the instrument is the one-generation-lagged ethnic diversity of the population. Starting from the simple model that includes only age covariates, we add deviation in the team minute appearances as well as the log of GDP per capita, population, and lagged immigration stocks.

Our estimate of the effect of diversity is positive in all our specifications. Its significance varies between 5% and 10% in the OLS columns, whereas results from the IV specifications indicate a positive coefficient, significant at the 5% level.

The under-identification Kleibergen-Paap rk LM test statistic (idstat) and the weak identification Kleibergen-Paap Wald rk F test statistic (widstat) both suggest that our instrument is strong. This second is the equivalent of the Cragg-Donald Wald F statistic for the case in which robust standard errors are used. As for the size of the effect, while OLS estimates present a coefficient of just below 3, the IV estimations imply that a one standard deviation increase of the diversity measure translates into an increase in the Elo score change between 20 to 32.2. Given that the in-sample standard deviation of the Elo score change is about 40, the IV results suggest a change of approximately one-half to three-quarters of a standard deviation in this outcome for a one increase in the standard deviation of ancestral diversity. To illustrate the size of our results, let us consider a couple of examples. At the end of the 2018 World Cup finals, Portugal's Elo score was 1940, Croatia's 1943, Germany's 1964, and Spain's 2010. A change of 32 points in the Elo score would make Portugal outrank Germany, climbing two positions in this ranking.

The deviation in minutes appearances is positive, suggesting that the players' strategic turnovers seem to matter for the teams' performance. This might reflect the fact that teams with a broader pool of good players perform better. Demographic aspects, such as past immigration and population, are positive but not significant factors, while GDP per capita appears to be a significant positive driver of performance in the IV specifications, suggesting that countries with more resources perform better.

As an alternative to our benchmark measure, the outcome of interest would involve taking the Elo score levels at the end of the championship stage (instead of the changes) and controlling for the initial score level. We perform this exercise in Table 1.4, and results are virtually unchanged.

1.5.2 Bilateral estimations

The baseline findings concerning the bilateral specification are in Table 1.5. They include robust standard errors, clustered at the match level. Team i is referred to as the home team and team j to the away team. [30] The dependent variable for this framework is the goal difference as we perform the analysis at match level. Similar to the previous section on unilateral estimations, the Table 1.5 presents results in the left panel (columns 1 to 5) where potential endogeneity concerns arise, and the IV results in the right panel (columns 6 to 10). Starting with the simplest specification that considers age covariates, results gradually control for variation in appearances, per capita GDP, population, and lagged immigrant stocks. Finally, Columns 5 and 10 add three gravity covariates at the bilateral level, namely, (current or historical) contiguity, sharing a common language, and belonging to the same country at some stage in time.[31] The significance of the coefficients is in line with those of the unilateral framework. Diversity is positive but not always significant in the OLS specifications (columns 1 to 5), while it becomes significantly positive at 5% level in all IV specifications. As we would expect, home team controls have either opposite signs compared with their away team counterpart or no significant role. Past immigration stocks, when significant, increase the relative team performance, suggesting an effect related to the enlargement of the talent pool. Although its significance drops in some specifications, GDP per capita is a positive determinant of performance, reflecting that teams from richer countries can benefit from better resources, which in turn improve performance.

Concerning the economic magnitude of our coefficient of interest, in the IV specifications, a one-standard-deviation increase in the diversity measure leads to an increase in the goal difference of between 0.7 to 1.4 units. While we address some specification concerns in the next paragraph, the evidence from the baseline results seems much in line with the unilateral framework.

[30] Note that, in the final stages, only hosting countries may play at home.

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

1.6 Robustness checks

In the following sections, we conduct a number of sensitivity exercises to assess the impact of our methodological options in the benchmark estimations. We first consider the robustness checks in the unilateral setting and then move to the bilateral framework.

1.6.1 Sensitivity checks in the unilateral analysis

To evaluate the sensitivity of our unilateral results, we conduct a set of robustness checks. We first introduce further controls in the unilateral regressions. We then check the robustness of the results obtained with our benchmark diversity measure. We further analyze how much our findings change if we highlight the coach's role by including controls at the level of the team's manager. Finally, since our principal analysis focuses on European teams, we assess the internal and external validity of the analysis. We therefore adjust the Elo score to consider intercontinental matches in the unilateral analysis in order to exclude the influence of matches with non-European teams.

Additional Controls

In the baseline estimation, we introduce two additional covariates of interest measured at the match level. The results are in Table 1.6. Specifically, we add the average adversary diversity and the average adversary strength measured by their average Elo score levels. In the regressions, we gradually add controls from left to right. In Column 5, we include these two covariates jointly. The IV results are in line with those in the benchmark regressions. The adversary's diversity is, in general, negatively correlated with the team's performance. Adversary's strength appears to impact the Elo score change positively. Nevertheless, this result likely comes from the score construction, which specifically gives weight to the strength of the adversary.

Checks on the diversity measure and IV

In Table 1.7, we perform a series of sensitivity checks regarding the diversity measure. The first three columns report the same results of Table 1.3 using an alternative diversity measure weighted by each player's minute appearance. The alternative diversity index, denoted $Divalt_{ist}$ takes the following form:

$$Divalt_{ist} = \frac{1}{S_t} \sum_{j=1}^{N_t} \sum_{k=1}^{N_t} pAPP_{jt} pAPP_{kt} d_{jk}, \ j \neq k \tag{1.6}$$

where $pAPP_{jt}, pAPP_{kt}$ are the shares of minute appearances of origin j and k respectively, belonging to the set of origins {1,...N_t} in team i for stage s of championship t. As for our baseline index, we normalize this expression by a team size factor S_t and include genetic distance d_{jk}. By giving more weight to the most active players, this alternative measure allows us to harmonize the size of a team when computing its diversity, excluding players who were listed but never called on the pitch. A discrepancy between these results and those from the benchmark regressions would possibly indicate whether players' diversity matters in the training stages rather than at the competition level itself. As in Table 1.7, the outcomes are virtually unchanged: the diversity coefficients are positive and in line with the previous results. This suggests that our findings are relevant at the competition level.

Column 5 of Table 1.7 checks sensitivity to the use of Spolaore and Wacziarg, 2009's baseline genetic distance, based on the majority ethnic groups, against their alternative indicator. The latter adjusts genetic distances with (time-invariant) data from Alesina et al., 2003 on ethnic group proportions. Crucially, this adjustment results in some missing values for a minority of country pairs ij, absent in Alesina et al., 2003's dataset. The two measures are highly correlated, and Spolaore and Wacziarg, 2009's results are not sensitive to this alternative measurement. Important for our diversity computation, completed cases in the country pairs ij are key to our diversity index construction (we have fewer missing values for our computation of the diversity measure). In Column 5, however, we present results from using this alternative distance indicator. In terms of controls, this specification is comparable to the results in columns (3) and (7) of Table 1.3. These columns represent a suitable comparison in that they display the most conservative results in Table 1.3. Results in Column (5) indicate a coefficient of about 1, significant at the 10 % level. While this suggests some sensitivity with respect to the chosen genetic distance measure, the coefficient of diversity remains significantly positive.

Finally, in the last two columns, we increase the lag of the instrument from 18 years to 20 (Column 6) and 22 (Column 7). The results are again comparable to columns (3) and (7) in Table 1.3. While availability of the data regarding the instrument with a larger lag time, neither the decrease in the sample size nor the different time lag affect the main results. The coefficient on diversity is slightly smaller than in the baseline (the coefficient of interest is 18.6 when considering a 20-year lag, and 14.8 with a 22-year lag). Here again, Kleibergen-Paap Wald rk F test and the LM test statistic support the relevance of the instrument in terms of strength.

Controlling for coach quality

We further test the robustness of ancestral diversity's positive effect on football performance by adding control variables that involve information on the team managers. It could be argued that coaches of high quality would also favor higher ancestral diversity because they anticipate its benefit on the performance. Failure to account for coach quality could, at least theoretically, confound the effect of ancestral diversity on team's performance. To account for such an effect, we supplement our set of controls with variables capturing the quality of the manager of national teams.

We retrieve the information on the team manager from the same source used to capture the national teams' squad composition. More specifically, we collect three pieces of information on the person reported as *Manager* in the squad list: age; nationality; and a measure of previous experience, defined as how many prior UEFA/FIFA Championships are listed in the coach's career details. We approximate the age by the difference between the Cup year and the birth year. Furthermore, we create a dummy capturing whether the coach's nationality is different from that of the national team or not. The use of a foreign coach is clearly a measure of quality since countries have a natural bias to choose a native coach for managing their national squad. In a small number of cases where information is missing from the source, some information was added manually if available via other sources.[32]

We also construct a measure of coach quality based on coach awards. We consider two awards: the European Football Coach of the Season, and the European Football Coach of the Year. These awards are annual prizes organized by European Press or technical entities (depending on the year, the European Union of Sports Press, Association of European Journalists, UEFA, Technical Commission of Torneo di Viareggio). We extract the winner's name information from Wikipedia[33] and set a dummy equaling 1 whenever (after spelling checks) the winner of these awards was a manager included in our sample.

We add this set of controls in the sensitivity checks above and present the results of these estimations in Table 1.8. The significance of the diversity variable (first row of the table results) remains unchanged, and the point estimate of the coefficient is strongly comparable to the benchmark estimates. We find coach variables to be weak predictors of the Elo score-based performance. The coach's past experience is significant in only two specifications, and its effect sign is negative. The foreign coach dummy is associated with a positive coefficient, albeit not always significant in a subset of specifications.

The European Tournament: internal and external validity

Our analysis focuses on teams affiliated with the UEFA, the European authority of football. This choice was motivated mainly by the availability of data concerning the composition of squads. This implies some restrictions on the sample of countries that we consider. Thränhardt, 1992 documents how Europe has become an immigration continent in the recent decades and details how these flows display cross-country and over time variations. This motivates our focus on Europe, as well as our long

[32] For coaches whose age was not found, we approximate the age as the year average. The exact information is missing for the following coaches: Andreas Lazaridis, Guentcho Dobrev, Ilia Shuke, José Gomes da Silva, Takis Charalambous, and Tony Formosa.

[33] Wikipedia, "European Football Coach of the Season," "European Football Coach of the Year." https://en.wikipedia.org/wiki/European Football Coach of the Season, https://en.wikipedia.org/wiki/European Football Coach of the Year

panel construction. In the conflict literature, Arbatlı et al., 2020 limit the geographic baseline coverage of their study to Europe, Asia and Africa to maintain low levels of admixture in distant national populations. Arbatlı et al., 2020 and previously Ashraf and Galor, 2013 identify the distance from Addis Ababa in East Africa as a strong predictor of the historical degree of genetic diversity of a national population. Spolaore and Wacziarg, 2016 observe that genetic distances effectively summarize differences in intergenerationally transmitted human traits, but best correlate with language disparities in the Old World.

Therefore, the restrictions in our choices are also motivated by comparability concerns in terms of the ancestral diversity of the native population. We build our diversity measures so that two team members from the same surname-predicted origin do not contribute differently to the overall team's ancestral diversity. This assumption is likely to be restrictive in the New World if surnames' transmission doesn't reflect population relatedness. Further, European countries' geographic proximity allowed us to maintain greater comparability of the native groups' levels of ancestral diversity.[34] This might imply that the national teams across countries' ancestral diversity levels mostly result from immigration patterns rather than ancestral variation in the indigenous population. This said, we acknowledge that extending the same analysis to other Continents may produce technical difficulties, and we cannot conclude that external validity concerns do not arise.

In the World Cup final stage, qualified UEFA teams meet finalists from UEFA and from other continents. These intercontinental matches are not considered in the baseline specifications, as we do not have data about the opponents for those games. Conceptually, this sample exclusion is likely to be positively correlated with performance, in the sense that this circumstance would arise only with World Cup finalists. On the other hand, diversity coefficients would be biased by this exclusion if, given the controls, diversity was somehow correlated with the probability of excluding the team match. For instance, this could happen in case of a misspecification of the linearity of the effect. Suppose there is a marginally decreasing effect of diversity on performance (green curve of Figure 1.7), for which the linear model that we use constitutes a linear approximation (blue line). The truncation of high performing teams' matches in the World Cup finals can lead to an upward bias (see the higher slope from the red line) in the estimated effect of diversity.

We do not find any evidence of a possible quadratic effect of diversity in our OLS specifications.[35] In our Unilateral specification, we can further test whether our outcomes are preserved if the performance measure also includes matches against inter-continental teams. We reproduce the unilateral results of Table 1.3, but we replace the outcome variable Elo' score change that we compute, with the equivalent measure directly obtained from *eloratings.net*. Crucially, in this alternative outcome

[34] Note the low levels of genetic distances across populations in the European Continent table in Cavalli-Sforza et al., 1994.

[35] Results are not presented here in the interest of space but are available upon request.

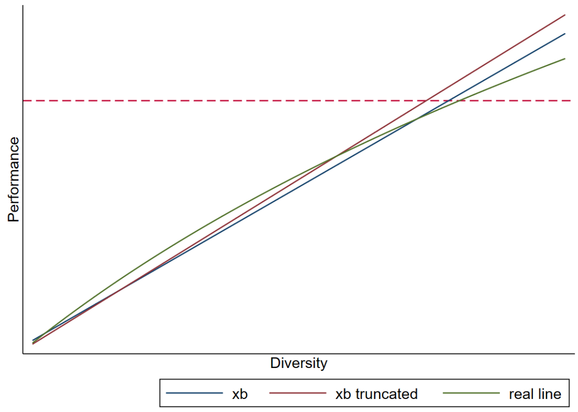

Figure 1.7: Upward bias in the effect of diversity from misspecification and sample composition.

Notes: Simulation example: 2000 observations. Data generating process for y: 0.9*log(0.6*x+0.2)+1.1. The xb line represent the slope from a regression of x on y. The xb truncated line represents the slope from a regression of x on y, in a subset of observations for which y is below .8 (approximately 83% of the initial sample observations). This graph shows a higher slope resulting from this top-truncation.

variable, all championship matches are included. Concerns would arise if our results of this alternative set of regressions were not in line with the baseline ones, as this could possibly indicate an upward bias in the bilateral setting. As Table 1.9 reflects, results are virtually unchanged by this modification. The coefficient for diversity ranges from roughly 17 to 27 in the IV, while it is roughly 3.5 in the OLS.

1.6.2 Sensitivity checks in the bilateral estimations

Similar to the unilateral analysis, we perform a series of robustness checks in our specifications conducted at the match level.

Additional controls

To better assess the match-level dimension of this result, we add the relative teams' initial Elo score levels as a control. In Table 1.10, we present results that complement the previous outcomes with this additional control. As one could expect, initial scores of the teams are positive predictors of their relative performance. Nevertheless, the effect of diversity remains significantly positive in all the IV-based results, as in the benchmark. This suggests that diversity has a distinctive role in performance during the match, and that positive skill complementarity is involved in the team's coordination.

Alternative regression methods

We assess the robustness of several methodological choices made in the regression analysis within the bilateral framework. We first carry out some sensitivity checks with respect to the way performance is measured. We follow a comparable approach to the unilateral specifications. Columns (1) to (4) of Table 1.11 report the results of, respectively, a specification where diversity is replaced with its appearance's re-weighted measure; a regression where diversity is computed with the alternative genetic distance measure as proposed in Spolaore and Wacziarg, 2009; and of two specifications with alternative lags for our instrument (20 years and 22 years). The resulting coefficients are very comparable to the baseline evidence.

A second check concerns the use of linear regression models. Since the goal difference is a discrete variable (ranging between –13 and 12), the linear models may become less appropriate as they assume a continuous variable. We address this concern in two different ways. First, we perform an inverse hyperbolic sine (IHS) transform to the variable. This type of procedure has been proposed in the literature by Burbidge et al., 1988 as an alternative to the log transformation. Indeed, such a transformation allows for the inclusion of variables that take zeroes and negative values, while maintaining approximatively the same interpretation of the coefficient as the log form. Second, we conduct a Poisson-based regression with scores as our outcome of interest. Results from Column (5) suggest that a hyperbolic sine transformation does not lead to different outcomes in the results of interest: a positive coefficient for the diversity measure of roughly 0.57 is significant at 1% level. Column (6) of Table 1.11 estimates a linear model on the number of goals at home as dependent variable. The coefficient on diversity is significant at 5% level and approximately 0.56.

Finally, an alternative specification on the bilateral diversity is proposed. Instead of the benchmark bilateral diversity measure corresponding to the difference $(Diversity_{home} - Diversity_{away})$ we allow the two terms to enter separately, allowing for the presence of a different effect for the home team and away team. Each term is instrumented (resulting in two first stages). Results indicate coefficients with opposite signs: the goal difference is, as expected, impacted positively by the home team and negatively by the adversary, with significance at a 5% level.

Number of goals as performance indicator

We further check the robustness of our results by using the number of goals scored or taken as alternative measures of the team's performance. We accommodate the discrete and non-negative nature of such an outcome by using a count data model estimated by Poisson. To account for endogeneity concerns, we use a control function approach (see for instance Lin and Wooldridge, 2019 for a discussion of the relevance of this approach, and Miroudot and Rigo, 2021 for an application of the technique to a gravity model setting). Table 1.12 presents average marginal effects of diversity on the two teams' outcomes considered separately. In Appendix 1.E, we also present the estimated coefficients from the structural equation and the results of the first stages obtained through this approach.

Our dependent variable is the number of goals made by the home team in one set of regressions and by the away team in a second set of regressions. Such an outcome is a discrete and non-negative count variable, which encourages our choice for a Poisson second stage. We follow the procedure suggested by Lin and Wooldridge, 2019 and use the two diversity measures separately, as the outcome variables are also team specific.

We have two separate first stages, one for each of the two variables of interest (diversity$_i$ and diversity$_j$). We include team$_i$ plus team$_j$ fixed effects and time fixed effects. We bootstrap standard errors in both stages with 2000 repetitions, and cluster them at the ij pair (unordered, i.e., ij=ji). The control function approach plugs the residuals of the first stage into the second, rather than the fitted values. This conveniently avoids inserting estimated fixed effects in the second equation, which is of exponential form for our specification.
We standardize our regressors of interest to simplify the interpretation of the partial effects and present average marginal effects (AME) in Table 1.12. The full table of coefficients is found in Appendix 1.E for the sake of completeness (Table 1.E.1 and 1.E.2). We maintain the same five different sets of controls to compare with the benchmark.

The AME results suggest an effect broadly in line with our previous findings. As the top part of Table 1.12 displays, the diversity of the home team (respectively, away team) when the effect is significant and positively (respectively, negatively) affects its performance. The diversity of the opponent negatively affects it. The expected goal count increases from 0.43 to 0.52 (columns 1 to 3) for a given increase of a standard deviation increase in the home team diversity, while it decreases by roughly the same amounts, from 0.375 to 0.63 (columns 3, 4, and 5) for a given increase of the away team diversity. Results are broadly similar in the away score specifications, shown at the bottom of Table 1.12. In this specification, however, it is only the relative team's diversity that significantly (and positively) affects its performance.

Controlling for coach information

Akin to the sensitivity checks performed in the unilateral regressions, we further test the robustness of our bilateral results by adding variables capturing information about the teams' managers. Table 1.13 documents the results. As in the unilateral framework, we control for age, tenure, a foreign nationality dummy, and a measure of coach quality for both the home and the away team. In this set of regressions, the away team's foreign coach dummy is positively associated with the away team performance, as is the coach quality measure (based on awards). A positive and significant coefficient associated with our diversity measure is maintained in our IV regressions.

1.7 Placebo analysis

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

For the sake of this analysis, we extract information from Wikipedia about the total number of medals and gold medals won by each nation in the European Athletics Indoor Championships[36] and the European Athletics Outdoor Championships,[37] The European Athletics Outdoor Championships is an athletics event that started in 1934 with a quadrennial frequency until 2010 when it switched to a biennial frequency.[38]
The number of athletes that each national federation can enroll in any of these championships is based on their performance and is capped from above for each nation and discipline.[39]

As noted above, we collect information on the number of medals each nation won in each championship. To match these data with our original biennial data of football events, we consider athletics championships held in year t (if t is an odd year) as having been held in $t+1$. Whenever we have more than one event in the same year, we average the total medals won by a nation by year. We therefore obtain two indicators of athletic performance at national level: the number of total medals obtained by the national representatives, and the number of gold medals. The results of the placebo exercise are reported in tables 1.E.5, 1.E.6 and 1.E.7. Specifically, Table 1.E.5 serves as a direct comparison and presents results from our regressions on our benchmark outcome. In these tables, different from our baseline,

[36] Wikipedia, "European Athletics Indoor Championships." https://en.wikipedia.org/wiki/European Athletics Indoor Championships.

[37] Wikipedia, "European Athletics Championships." https://en.wikipedia.org/wiki/European Athletics Championships.

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

[39] European Athletics, "Competition regulations," https://european-athletics.com/competition-regulations/.

we control for population, as we deem it an essential covariate for our athletics-based tables. Table 1.E.6 shows placebo results when the dependent variable is the number of total medals; Table 1.E.7 presents results when the dependent variable is the number of gold medals.

Coefficients of our diversity score in tables 1.E.6 and 1.E.7 turn out to be insignificant, suggesting that diversity in football teams does not impact the performances of an individual sport such as athletics. All in all, this strengthens the case of a positive impact of ancestral diversity through its impact on collective performance through the generated complementarity of skills.[40]

1.8 Conclusion

Diversity is a double-edged sword. Greater diversity is beneficial in teamwork since teams can draw on a larger variety of skills and knowledge from a diverse group of people. However, diversity might also lead to decreased team performance and team effectiveness if more diversity brings lack of coordination and increased conflict. In this paper, we assess the effect of ancestral diversity, due to past migration flows, on sport performance. To do so, we have built a new dataset that brings together information about the ancestral diversity of European national football teams playing in the World Cup or European Cup, qualifications and finals, and several time-varying performance indicators for each national team. Ancestral diversity of players may lead to a lack of team spirit on the one hand but, on the other hand, may lead to innovative ways to play. In addition, it is well known that some football-specific skills (e.g., endurance capacity, muscle performance, height, or technical skills) are related to ancestral background (see Lippi et al., 2010). Therefore, ancestral diversity boosts complementarities among players holding different positions on the football team. Hence, overall, we expect ancestral diversity to improve sportive performance. This is confirmed in our analysis. We establish a positive causal relationship between this measure of team diversity and both a team's Elo score and the probability of winning a match. We also prove that this diversity benefits teams beyond any effect stemming from population size, GDP per capita, coach experience, and other factors. The result is quite large and not negligible. Analyzed using a variety of perspectives, and taking into account endogeneity and measurement error concerns via an instrumentation method, the overall evidence produced in our specifications strongly suggests that diversity enhances performance at match level-as proxied by the goal difference-and translates into higher overall team (Elo) scores at the end of the championship.

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

Our findings complement the flourishing but limited literature on countries' diversity that accounts for intergenerational transmission of traits and its corresponding effects. Our contribution is a novel one as it focuses on the sports team. The results are robust to a large list of checks where we use variation of the diversity measure and of the instrument. We also perform a placebo test to rule out any remaining concerns about some omitted variable, such as the presence of a particular set of origins that would positively affect the national talent pool and our national team diversity. In the placebo test, we show that, as expected, ancestral diversity does not affect the performance of national athletics teams because each athlete competes individually rather than within a team.

Our study is not intended to be a biological one. We examine the effect on performance today of deep-rooted values and traits shaped across generations. Differences in these characteristics and the associated information they bear, proxied by genetic distances, cannot be captured (or measured) by simple country fixed effects or other cultural and institutional characteristics formed in humanity's more recent history. It is important to stress that our results do not carry any implications in terms of superiority or inferiority of particular genetic information of specific origins over other ones. Rather, our interest is on the inherited diversity among the players on a team and how these differences translate into a comparative advantage at the *team level* in sportive performance and innovative play. We find, in fact, that different deep-seated factors embodied by the genetic distances do matter.

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

1.9 Tables section

Note: additional tables are presented in appendices 1.D and 1.E.

Table 1.1: Summary statistics table, unilateral framework

	Mean	Standard Deviation	N	Min	Max
Elo score changes, computed	0.298	40.129	1900	-216.075	181.142
Elo score, computed	1671.196	234.233	1900	873.050	2157.986
Performance measures					
Elo score	1692.840	232.887	1900	852.000	2223.000
Elo score changes	0.897	45.753	1900	-233.000	217.000
Diversity measures					
Diversity	0.033	1.028	1900	-0.681	6.777
Diversity, appearance	0.031	1.028	1900	-0.629	8.371
Diversity, SW	2.257	2.557	1900	0.000	19.576
Team level variables					
Adversary's diversity	0.007	1.008	1900	-1.126	10.047
Adversary's strength	1700.037	117.043	1900	1411.171	2140.289
Foreign coach	0.176	0.381	1900	0.000	1.000
Coach age	50.669	8.089	1900	28.000	74.000
Coach award	0.083	0.275	1900	0.000	1.000
Stand. dev. appearances	191.678	65.702	1900	59.594	451.440
Stand. dev. squad age	3.611	0.636	1900	1.953	6.214
Squad age	27.554	1.004	1900	24.286	31.045
Squad age, squared	760.240	55.366	1900	589.796	963.820
Squad size	30.091	8.049	1900	15.000	59.000
Macroeconomic variables					
Log immig. stocks, 18y lag	12.444	2.623	1676	0.000	16.294
Log of GDP/capita	9.669	1.034	1900	6.836	11.584
Population (mln)	23.253	27.975	1900	0.025	148.336
IV					
IV, 18y lag	-0.000	1.000	1900	-0.980	4.073

Notes: The unilateral specification involves a dataset of national teams appearing once for each stage of the tournament, World Cup or EURO Cup, for each of the years considered. Note that the team appears as an observation in this dataset even when it did not participate in that stage (qualification or final) to avoid dropping its information. When a country did not qualify for the finals, the levels of the explanatory variables will be equal to those at the end of the qualification stage. Similarly, its Elo score will be unchanged.

Table 1.2: Summary statistics table, bilateral framework

	Mean	Standard deviation	N	Min	Max
Performance measures					
Goal difference	0.482	2.068	3877	-8.000	11.000
Goal difference, hyperbolic sine	0.276	1.223	3877	-2.776	3.093
Diversity measures					
Bilateral diversity	0.002	1.044	3877	-5.382	5.569
Bilateral diversity, appearance	0.001	1.042	3877	-6.741	5.364
Bilateral diversity, SW	0.001	1.038	3877	-5.004	5.647
Diversity, home	0.051	1.047	3877	-0.698	6.850
Diversity, away	0.050	1.042	3877	-0.702	7.061
Team level variables					
Stand. dev. squad age, home	3.686	0.884	3877	1.953	13.278
Squad age, home	27.659	1.030	3877	24.286	31.045
Stand. dev. squad age, away	3.683	0.884	3877	1.953	13.278
Squad age, away	27.670	1.028	3877	24.286	31.045
Squad age, squared, home	766.094	56.999	3877	589.796	963.820
Squad age, squared, away	766.702	56.886	3877	589.796	963.820
Stand. dev. appearances, home	236.287	63.793	3877	59.594	451.440
Stand. dev. appearances, away	235.348	64.335	3877	67.750	451.440
Foreign coach, home	0.176	0.381	3877	0.000	1.000
Foreign coach, away	0.178	0.383	3877	0.000	1.000
Coach age, home	51.126	8.118	3877	28.000	74.000
Coach age, away	51.194	8.117	3877	28.000	74.000
Macroeconomic variables					
Population (mln), home	24.493	29.011	3877	0.224	148.689
Population (mln), away	24.263	29.025	3877	0.224	148.689
Log of GDP/capita, home	9.692	1.028	3877	6.836	11.584
Log of GDP/capita, away	9.682	1.033	3877	6.836	11.584
Log immig. stocks, 18y lag, home	12.665	2.461	3576	0.000	16.294
Log immig. stocks, 18y lag, away	12.630	2.459	3576	0.000	16.294
Adversary's strength, home	1674.520	108.400	3877	1416.287	2117.771
Adversary's strength, away	1673.245	111.092	3877	1400.824	2140.289
Contiguity	0.095	0.293	3877	0.000	1.000
Same nation	0.021	0.144	3877	0.000	1.000
Common language	0.050	0.219	3877	0.000	1.000
IV					
IV, home vs. away	0.000	1.000	3877	-3.631	3.646

Notes: The Bilateral specification involves a dataset of matches held in the qualification and final stages of the EURO or World Cup, where both adversaries belong to the UEFA affiliation.

Table 1.3: Football performance and ancestral diversity of national teams: unilateral estimations

	Dependent variable: change in rating of national football team (Elo score)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Variable of interest								
Diversity	2.974**	2.673**	2.807**	2.695*	22.288**	20.814**	23.652**	32.202**
	(1.142)	(1.156)	(1.129)	(1.387)	(10.567)	(10.273)	(11.655)	(16.299)
Control variables								
Stand. dev. appearances		0.276***	0.277***	0.310***		0.291***	0.293***	0.318***
		(0.023)	(0.023)	(0.028)		(0.026)	(0.027)	(0.032)
Log of GDP/capita			8.814	9.701			18.034**	16.642*
			(6.494)	(7.755)			(8.061)	(8.983)
Population (mln)			0.322				0.140	
			(0.208)				(0.414)	
Log immig. stocks, 18y lag				-0.496				1.356
				(1.371)				(1.781)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					20.34	20.31	17.47	11.83
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 1.4: Football performance and ancestral diversity of national teams: alternative measure of rating

	Dependent variable: Ending rating of national football team (Elo score)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Variable of interest								
Diversity	2.906**	3.372**	3.445**	3.869**	26.615**	25.199**	23.073**	38.367**
	(1.238)	(1.089)	(1.078)	(1.185)	(10.643)	(10.404)	(11.130)	(16.987)
Control variables								
Elo's inital levels, computed	0.869***	0.872***	0.871***	0.854***	0.871***	0.869***	0.868***	0.852***
	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.016)
Stand. dev. appearances		0.139***	0.140***	0.134***		0.295***	0.297***	0.315***
		(0.016)	(0.016)	(0.017)		(0.026)	(0.025)	(0.032)
Log of GDP/capita			8.002	3.930			17.064**	12.863
			(6.424)	(7.929)			(7.740)	(9.251)
Population (mln)			0.607*				0.502	
			(0.349)				(0.399)	
Log immig. stocks, 18y lag				1.380				3.425*
				(1.637)				(1.842)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					20.54	20.51	17.44	11.89
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 1.5: Goal difference and ancestral diversity: bilateral estimations

	Dependent variable: goal difference									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	IV	IV	IV	IV	IV
Variable of interest										
Bilateral diversity	0.091*	0.034	0.031	0.035	0.035	0.720**	0.969**	0.942**	1.414**	1.408**
	(0.047)	(0.044)	(0.044)	(0.045)	(0.045)	(0.297)	(0.342)	(0.299)	(0.512)	(0.511)
Control variables										
Log of GDP/capita, home		0.136	0.137	-0.010	-0.013		0.465*	0.459*	0.145	0.142
		(0.195)	(0.195)	(0.208)	(0.208)		(0.243)	(0.235)	(0.258)	(0.257)
Log of GDP/capita, away		-0.729***	-0.727***	-0.471**	-0.478**		-1.111***	-1.097***	-0.758**	-0.763**
		(0.198)	(0.198)	(0.214)	(0.214)		(0.252)	(0.242)	(0.285)	(0.285)
Population (mln), home			-0.005*					-0.002		
			(0.003)					(0.003)		
Population (mln), away			0.000					-0.003		
			(0.003)					(0.003)		
Log immig. stocks, 18y lag, home				0.068	0.067				0.154**	0.153**
				(0.044)	(0.044)				(0.062)	(0.061)
Log immig. stocks, 18y lag, away				-0.097**	-0.097**				-0.158**	-0.158**
				(0.046)	(0.046)				(0.057)	(0.057)
Observations	3877	3877	3877	3568	3568	3877	3877	3877	3568	3568
Kleibergen-Paap LM test						0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test						31.46	24.52	32.29	14.48	14.49
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Geo-political controls					Yes					Yes

Notes: Baseline stimates for the bilateral framework (match-level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970-2018 (for columns 1-3,6-8) / years 1978-2018 (in columns 4-5 and 8-9). Dependent variable: Goal difference. In all regressions, we include Team and year fixed effects, as well as a stage dummy. Column 1 to Column 5 display OLS results, with heteroskedastic robust standard errors in parentheses, clustered at Team pair level. Column 5 to Column 8 display IV results, with heteroskedastic robust standard errors in parentheses, clustered at Team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F-test for weak instruments. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Table 1.6: Football performance and ancestral diversity: further controls

	Dependent variable: change in rating of national football team (Elo score)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	IV	IV	IV	IV	IV
Variable of interest										
Diversity	2.974**	3.247**	2.288*	2.136	2.219	22.288**	27.755**	23.339*	32.172*	33.295*
	(1.142)	(1.067)	(1.247)	(1.532)	(1.515)	(10.567)	(12.685)	(11.931)	(17.383)	(17.595)
Control variables										
Log of GDP/capita		6.968	8.760	9.752	9.472		17.415**	18.029**	16.641*	16.461*
		(6.770)	(6.502)	(7.787)	(7.792)		(8.464)	(8.046)	(8.988)	(9.059)
Population (mln)		0.219	0.304				0.004	0.132		
		(0.232)	(0.208)				(0.422)	(0.411)		
Adversary's diversity		-1.326			-1.671		-2.664**			-2.308*
		(1.258)			(1.191)		(1.293)			(1.242)
Adversary's strength			0.022**	0.021**	0.026**			0.011	0.000	0.006
			(0.008)	(0.009)	(0.009)			(0.014)	(0.020)	(0.019)
Stand. dev. appearances			0.280***	0.313***	0.311***			0.296***	0.318***	0.316***
			(0.023)	(0.028)	(0.028)			(0.027)	(0.034)	(0.034)
Log immig. stocks, 18y lag				-0.596	-0.516				1.353	1.529
				(1.395)	(1.397)				(1.853)	(1.882)
Observations	1900	1900	1900	1676	1676	1900	1900	1900	1676	1676
Kleibergen-Paap LM test						0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test						20.34	16.93	16.72	10.27	10.05
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates for the unilateral framework. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3, 6–8) / years 1978–2018 (in columns 4–5, 8–9). Dependent variable: changes in the Elo score of the national team (end vs. beginning of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display OLS results, with heteroskedastic robust standard errors in parentheses, clustered at team level. Columns 5–8 display IV results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.7: Football performance and ancestral diversity: robustness checks

	Dependent variable: change in rating of national football team (Elo score)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV: Diversity, appearance	**IV:**Diversity, appearance	**IV:**Diversity, appearance	**IV:**Diversity, appearance	**IV:**Diversity, SW	**IV:** 20 years lag	**IV:** 22 years lag
Variable of interest							
Diversity, appearance	25.715**	23.998*	29.340*	33.358*			
	(12.887)	(12.505)	(15.426)	(18.091)			
Diversity, SW					10.975*		
					(5.806)		
Diversity						18.603*	14.854*
						(9.675)	(8.017)
Control variables							
Stand. dev. appearances		0.294***	0.296***	0.324***	0.292***	0.306***	0.309***
		(0.027)	(0.028)	(0.033)	(0.028)	(0.027)	(0.027)
Log of GDP/capita			20.526**	15.058*	23.217**	11.060	8.896
			(9.179)	(8.917)	(10.208)	(7.583)	(7.497)
Population (mln)			0.052		0.056	0.118	0.109
			(0.477)		(0.454)	(0.380)	(0.404)
Log immig. stocks, 18y lag				2.388			
				(2.282)			
Observations	1900	1900	1900	1676	1900	1784	1670
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	15.33	15.29	12.29	9.95	9.88	20.54	24.29
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates for the unilateral framework. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (columns 1–3, and 5) / years 1978–2018 (in Column 4) first year available for the instrument to 2018 (columns 6 and 7). Dependent variable: changes in the Elo score of the national team (end vs. beginning of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–8 display IV results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.8: Football performance and ancestral diversity: accounting for coach information

	Dependent variable: change in rating of national football team (Elo score)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Variable of interest								
Diversity	3.079**	2.741**	2.855**	2.800**	24.766**	23.279**	25.348**	34.327**
	(1.168)	(1.154)	(1.120)	(1.378)	(10.611)	(10.327)	(11.529)	(16.339)
Control variables								
Coach age	-0.111	-0.130	-0.119	-0.170	-0.053	-0.073	-0.043	-0.056
	(0.172)	(0.160)	(0.165)	(0.159)	(0.172)	(0.164)	(0.167)	(0.197)
Coach tenure	-0.963	-0.898	-0.990	-0.959	-1.123	-1.019	-1.162*	-1.311*
	(0.718)	(0.669)	(0.675)	(0.686)	(0.708)	(0.672)	(0.678)	(0.785)
Coach award	4.294	2.188	2.112	3.372	5.105	2.938	2.915	4.409
	(4.583)	(4.653)	(4.777)	(4.991)	(4.489)	(4.391)	(4.513)	(5.085)
Foreign_coach==1	5.592*	4.308	3.971	4.426	6.404**	4.951	4.092	5.343
	(2.817)	(2.676)	(2.646)	(2.850)	(3.254)	(3.069)	(3.087)	(3.542)
Stand. dev. appearances		0.274***	0.275***	0.307***		0.288***	0.290***	0.312***
		(0.023)	(0.023)	(0.029)		(0.027)	(0.027)	(0.033)
Log of GDP/capita			8.616	9.274			18.635**	16.656*
			(6.704)	(8.102)			(8.111)	(9.154)
Population (mln)			0.410*				0.215	
			(0.216)				(0.425)	
Log immig. stocks, 18y lag				-0.556				1.403
				(1.435)				(1.800)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					20.62	20.60	17.63	11.97
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 1.9: Football performance and ancestral diversity: accounting for intercontinental matches

	Dependent variable: change in rating of national football team (Elo score); scores from websource							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Variable of interest								
Diversity	3.690^{**}	3.355^{**}	3.417^{**}	3.531^{**}	18.984^{*}	17.341^{*}	21.404^{*}	27.353^{*}
	(1.272)	(1.126)	(1.112)	(1.302)	(10.390)	(9.929)	(11.711)	(15.457)
Control variables								
Stand. dev. appearances		0.307^{***}	0.307^{***}	0.352^{***}		0.325^{***}	0.326^{***}	0.364^{***}
		(0.027)	(0.028)	(0.032)		(0.032)	(0.032)	(0.036)
Log of GDP/capita			3.483	-1.976			11.483	3.702
			(6.749)	(7.308)			(8.679)	(9.004)
Population (mln)			0.074				-0.083	
			(0.189)				(0.402)	
Log immig. stocks, 18y lag				1.379				2.872
				(1.385)				(1.805)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					0.00	0.00	0.00	0.00
Kleibergen-Paap F test					20.34	20.31	17.47	11.83
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 1.10: Goal difference and diversity: controlling for initial strength

	Dependent variable: goal difference									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	IV	IV	IV	IV	IV
Variable of interest										
Bilateral diversity	0.094**	0.041	0.039	0.039	0.039	0.612**	0.897**	0.861**	1.315**	1.309**
	(0.046)	(0.043)	(0.043)	(0.045)	(0.045)	(0.272)	(0.319)	(0.277)	(0.476)	(0.474)
Control variables										
Initial Elo score, home	0.002***	0.001**	0.001**	0.001**	0.001**	0.002***	0.001***	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Initial Elo score, away	-0.002***	-0.001***	-0.001***	-0.001**	-0.001**	-0.002***	-0.001***	-0.001***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of GDP/capita, home		0.167	0.168	0.039	0.038		0.476**	0.466**	0.207	0.205
		(0.195)	(0.195)	(0.207)	(0.207)		(0.237)	(0.230)	(0.251)	(0.251)
Log of GDP/capita, away		-0.759***	-0.757***	-0.517**	-0.522**		-1.110***	-1.092***	-0.790**	-0.794**
		(0.197)	(0.197)	(0.214)	(0.214)		(0.244)	(0.235)	(0.277)	(0.276)
Population (mln), home			-0.004					-0.001		
			(0.003)					(0.003)		
Population (mln), away			-0.001					-0.004		
			(0.003)					(0.003)		
Log immig. stocks, 18y lag, home				0.051	0.050				0.121**	0.120**
				(0.044)	(0.044)				(0.057)	(0.057)
Log immig. stocks, 18y lag, away				-0.080*	-0.081*				-0.135**	-0.135**
				(0.046)	(0.046)				(0.054)	(0.054)
Observations	3877	3877	3877	3568	3568	3877	3877	3877	3568	3568
Kleibergen-Paap LM test						0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test						31.87	25.31	33.49	15.26	15.27
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Geo-political controls					Yes					Yes

Notes: Estimates for the bilateral framework (match-level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970-2018 (for columns 1-3,6-8) / years 1978-2018 (in columns 4-5 and 8-9). Dependent variable: goal difference. In all regressions, we include Team and year fixed effects, as well as a stage dummy. Column 1 to Column 5 display OLS results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. Column 5 to Column 8 display IV results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F-test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.11: Bilateral framework, further results

	Dependent variable: goal difference				hyperbolic sine	home score	goal difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV: Diversity, appearance	**IV:** Diversity, SW	**IV:** 20 years lag	**IV:** 22 years lag	**IV:**Goal difference, hyperbolic sine	**IV:**Outcome: home score	**IV:**Diversity, home vs. away
Variable of interest							
Bilateral diversity			0.888***	0.793***	0.573***	0.556**	
			(0.269)	(0.237)	(0.172)	(0.229)	
Bilateral diversity, appearance	1.125**						
	(0.368)						
Bilateral diversity, SW		1.065**					
		(0.354)					
Diversity, home							0.726**
							(0.296)
Diversity, away							-0.651**
							(0.278)
Control variables							
Population (mln), home	-0.004	-0.001	-0.002	-0.004	-0.000	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Population (mln), away	-0.002	-0.004	-0.003	-0.002	-0.002	0.000	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Log of GDP/capita, home	0.577**	0.596**	0.445*	0.411*	0.272**	0.292*	0.475*
	(0.262)	(0.267)	(0.231)	(0.221)	(0.139)	(0.163)	(0.266)
Log of GDP/capita, away	-1.124***	-1.208***	-1.020***	-0.908***	-0.422**	-0.918***	-1.083***
	(0.251)	(0.276)	(0.232)	(0.226)	(0.130)	(0.197)	(0.256)
Finals==QUALI	0.568***	0.544***	0.569***	0.537***	0.284***	0.453***	0.550***
	(0.113)	(0.112)	(0.106)	(0.106)	(0.066)	(0.085)	(0.163)
Observations	3877	3877	3762	3643	3877	3877	3877
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	28.13	22.76	40.42	47.09	32.29	32.29	15.47
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 1.12: Bilateral framework, goals for, goals against

	Dependent variable: home team's goals scored				
	(1)	(2)	(3)	(4)	(5)
	IV: Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function
AMEs diversity away	-0.215	-0.393	-0.375*	-0.630*	-0.631*
	(0.215)	(0.249)	(0.222)	(0.345)	(0.346)
AMEs diversity home	0.436*	0.516*	0.542**	0.596	0.592
	(0.242)	(0.280)	(0.250)	(0.454)	(0.458)
	Dependent variable: away team's goals scored				
	(1)	(2)	(3)	(4)	(5)
	IV: Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function
AMEs diversity away	0.395**	0.434**	0.354**	0.489*	0.497*
	(0.171)	(0.193)	(0.169)	(0.280)	(0.281)
AMEs diversity home	-0.181	-0.204	-0.216	-0.485	-0.471
	(0.183)	(0.215)	(0.191)	(0.376)	(0.381)
Observations	3877	3877	3877	3568	3568
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: Average marginal effects. Estimates for the bilateral framework (match level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in columns 4–5). Dependent variable: home team's number of goals scored in the top sub-table, away team's number of goals scored in the top sub-table. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–5 display results from a Poisson, control-function regression, with bootstrapped (2000 reps) standard errors in parentheses, clustered at team pair level. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.13: Bilateral framework, controlling for coach quality

	Dependent variable: goal difference									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	OLS	IV	IV	IV	IV	IV
Variable of interest										
Bilateral diversity	0.091*	0.032	0.030	0.034	0.034	0.684**	0.960**	0.923**	1.354**	1.348**
	(0.047)	(0.044)	(0.044)	(0.045)	(0.045)	(0.291)	(0.342)	(0.295)	(0.498)	(0.497)
Control variables										
Coach tenure, home	0.014	0.004	0.004	0.012	0.012	0.007	-0.006	-0.006	-0.008	-0.008
	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.019)	(0.019)
Coach tenure, away	-0.018	-0.006	-0.006	0.005	0.005	-0.010	0.008	0.007	0.028	0.028
	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.019)	(0.019)
Coach age, home	-0.004	-0.005	-0.004	-0.006	-0.006	-0.002	-0.001	-0.001	0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Coach age, away	0.005	0.007	0.007	0.007	0.007	0.003	0.002	0.003	0.000	0.000
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Coach award, home	0.186*	0.122	0.106	0.078	0.074	0.187*	0.131	0.125	0.076	0.073
	(0.099)	(0.095)	(0.095)	(0.097)	(0.097)	(0.100)	(0.100)	(0.100)	(0.110)	(0.109)
Coach award, away	-0.335***	-0.243**	-0.243**	-0.243**	-0.246**	-0.348***	-0.270**	-0.283**	-0.265**	-0.267**
	(0.090)	(0.089)	(0.090)	(0.092)	(0.092)	(0.092)	(0.097)	(0.097)	(0.107)	(0.107)
Foreign coach, home	0.041	-0.024	-0.018	0.014	0.014	0.069	0.022	0.021	0.117	0.117
	(0.077)	(0.074)	(0.074)	(0.078)	(0.077)	(0.081)	(0.083)	(0.083)	(0.099)	(0.099)
Foreign coach, away	-0.239**	-0.143*	-0.143*	-0.204**	-0.202**	-0.246**	-0.148*	-0.142*	-0.247**	-0.245**
	(0.084)	(0.082)	(0.082)	(0.083)	(0.083)	(0.085)	(0.086)	(0.086)	(0.095)	(0.094)
Log of GDP/capita, home		0.135	0.136	-0.021	-0.024		0.461*	0.451*	0.128	0.124
		(0.197)	(0.197)	(0.209)	(0.209)		(0.245)	(0.236)	(0.257)	(0.256)
Log of GDP/capita, away		-0.669***	-0.668***	-0.412*	-0.420**		-1.065***	-1.047***	-0.705**	-0.711**
		(0.199)	(0.199)	(0.214)	(0.214)		(0.257)	(0.245)	(0.284)	(0.284)
Population (mln), home			-0.004					-0.001		
			(0.003)					(0.003)		
Population (mln), away			-0.000					-0.004		
			(0.003)					(0.003)		
Log immig. stocks, 18y lag, home				0.067	0.067				0.149**	0.149**
				(0.044)	(0.044)				(0.061)	(0.061)
Log immig. stocks, 18y lag, away				-0.091**	-0.092**				-0.153**	-0.152**
				(0.046)	(0.046)				(0.056)	(0.056)
Observations	3873	3873	3873	3568	3568	3873	3873	3873	3568	3568
Kleibergen-Paap LM test						0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test						30.97	24.22	32.21	14.64	14.65
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Geo-political controls					Yes					Yes

Notes: Estimates for the bilateral framework (match level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3, 6–8) / years 1978–2018 (in columns 4–5 and 8–9). Dependent variable: goal difference. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–5 display OLS results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. Columns 5–8 display IV results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Appendix

1.A The Elo formula

Updated at every match, the Elo score is computed as

$$R_n = R_o + K(W - W_e)$$

where R_n is the new rating, R_0 is the old (pre-match) rating. K is a constant weight for the tournament played: 60 for World Cup finals, 50 for the EUROs finals, 40 for World Cup and EURO qualifiers. K is then adjusted as follows for the goal difference in the game. It is increased by half if a game is won by 2 goals, by 3/4 if a game is won by 3 goals, and by $3/4 + (N - 3)/8$ if the game is won by 4 or more goals, where N is the goal difference.

W accounts for the game result (1 for a win, 0.5 for a draw, and 0 for a loss). W_e is the expected result:

$$W_e = \frac{1}{(10^{-\frac{dr}{400}} + 1)}$$

where dr equals the difference in ratings plus 100 points for a team playing at home. For a check on the similarity with the FIFA Ranking adopted after 2018 World Cup in Russia, please see the official FIFA publication: https://resources.fifa.com/image/upload/revision-of-the-fifa-coca-cola-world-ranking.pdf?cloudid=fzltr4s8tz3v3vy0aqo1.

1.B

Our prediction algorithm: examples

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

	SWEDEN TEAM, 2018 World Cup Finals
Andreas_Granqvist	Sweden
Emil_Forsberg	Sweden
Emil_Krafth	Sweden
Filip_Helander	Finland
Gustav_Svensson	Sweden
Isaac_Kiese_Thelin	Sweden
Jimmy_Durmaz	Turkey
Johan_Johnsson	Sweden
John_Guidetti	Italy
Kristoffer_Nordfeldt	Sweden
Ludwig_Augustinsson	Sweden
Marcus_Berg	Norway
Marcus_Rohdén	Sweden
Martin_Olsson	Sweden
Mikael_Lustig	Sweden
Ola_Toivonen	Finland
Oscar_Hiljemark	Sweden
Pontus_Jansson	Sweden
Robin_Olsen	Norway
Sebastian_Larsson	Sweden
Victor_Lindelöf	Sweden
Viktor_Claesson	Sweden

Notes: Example of predicted origins for the Belgian squad and the Swedish squad for the 2018 World Cup final stage.

	BELGIUM TEAM, 1990 World Cup Finals
Bruno_Versavel	Belgium
Enzo_Scifo	Italy
Eric_Gerets	Belgium
Filip_De_Wilde	Belgium
Franky_Van_Der_Elst	Belgium
François_De_Sart	Belgium
Georges_Grün	Germany
Gilbert_Bodart	Belgium
Jan_Ceulemans	Belgium
Lei_Clijsters	Belgium
Lorenzo_Staelens	Belgium
Marc_Degryse	Belgium
Marc_Emmers	Belgium
Marc_Wilmots	Belgium
Michel_De_Wolf	Belgium
Michel_Preud_homme	Belgium
Nico_Claesen	Belgium
Pascal_Plovie	Belgium
Patrick_Vervoort	Belgium
Philippe_Albert	Germany
Stéphane_Demol	Belgium

	SWEDEN TEAM, 1990 World Cup Finals
Anders_Limpar	Hungary
Glenn_Hysén	Sweden
Jan_Eriksson	Sweden
Joakim_Nilsson	Sweden
Johnny_Ekström	Sweden
Jonas_Thern	Sweden
Klas_Ingesson	Sweden
Lars_Eriksson	Sweden
Leif_Engqvist	Sweden
Mats_Gren	Sweden
Mats_Magnusson	Sweden
Niklas_Nyhlén	Sweden
Peter_Larsson	Sweden
Roger_Ljung	Sweden
Roland_Nilsson	Sweden
Stefan_Pettersson	Sweden
Stefan_Schwarz	Germany
Sven_Andersson	Sweden
Thomas_Ravelli	Italy
Tomas_Brolin	Sweden
Ulrik_Jansson	Sweden

Notes: Example of predicted origins for the Belgian squad and the Swedish squad for the 1990 World Cup final stage.

BELGIUM TEAM, 1970 World Cup Finals		SWEDEN TEAM, 1970 World Cup Finals	
Alfons_Peeters	Belgium	Björn_Nordqvist	Sweden
Christian_Piot	France	Bo_Larsson	Sweden
Erwin_Vandendaele	Belgium	Claes_Cronqvist	Sweden
Frans_Janssens	Belgium	Gunnar_Larsson	Sweden
Georges_Heylens	Belgium	Göran_Nicklasson	Sweden
Jacques_Beurlet	Belgium	Hans_Selander	Sweden
Jacques_Duquesne	Belgium	Inge_Ejderstedt	Sweden
Jan_Verheyen	Belgium	Jan_Olsson	Sweden
Jean_Dockx	Belgium	Krister_Kristensson	Sweden
Jean_Thissen	Netherlands	Kurt_Axelsson	Sweden
Léon_Jeck	Germany	Leif_Målberg	Sweden
Léon_Semmeling	Belgium	Ove_Grahn	Sweden
Marie_Trappeniers	Belgium	Ove_Kindvall	Sweden
Maurice_Martens	Belgium	Roland_Grip	Sweden
Nicolas_Dewalque	Belgium	Ronney_Pettersson	Sweden
Odilon_Polleunis	Belgium	Ronnie_Hellström	Sweden
Paul_Van_Himst	Belgium	Sten_Pålsson	Sweden
Pierre_Carteus	Belgium	Thomas_Nordahl	Norway
Raoul_Lambert	France	Tom_Turesson	Sweden
Wilfried_Puis	Belgium	Tommy_Svensson	Sweden
Wilfried_Van_Moer	Belgium	Örjan_Persson	Sweden

Notes: Example of predicted origins for the Belgian squad and the Swedish squad for the 1970 World Cup final stage.

1.C FIFA and UEFA

The inauguration of the FIFA World Cup championship was held in 1930. The first tournament was held in and won by Uruguay, and it was the only tournament for which no qualification stage was set. All countries affiliated with FIFA were invited to participate, and 13 countries accepted. Since then, the playing of the World Cup was established as every four years (with the exception of World War II breaks in 1942 and 1946), and a qualification process determined the final-stage participants. Both the number of participating countries and of qualified teams increased over time. Initially set at 16, the latter would increase to 24 in 1982, then to 32 in 1998, and will reach 48 in 2026.[41]

Relatively newer, the Union des Associations Européennes de Football (UEFA) was founded in 1954 and it organized the first European Nations' Cup (currently referred as to UEFA EUROs) in 1960. The Soviet Union won the first tournament in which 4 teams of 17 had made it to the final stage.[42] Here again, the number of teams selected for the final stages increased over time (8 teams in 1980, 16 in 1996, and 24 in 2016).

In terms of team squad members, there is an upperbound for the final

[41] For more details on the FIFA World Cup, see https://www.fifa.com/tournaments/mens/worldcup

[42] For more details on the UEFA EUROs, see https://www.uefa.com/uefaeuro/history/.

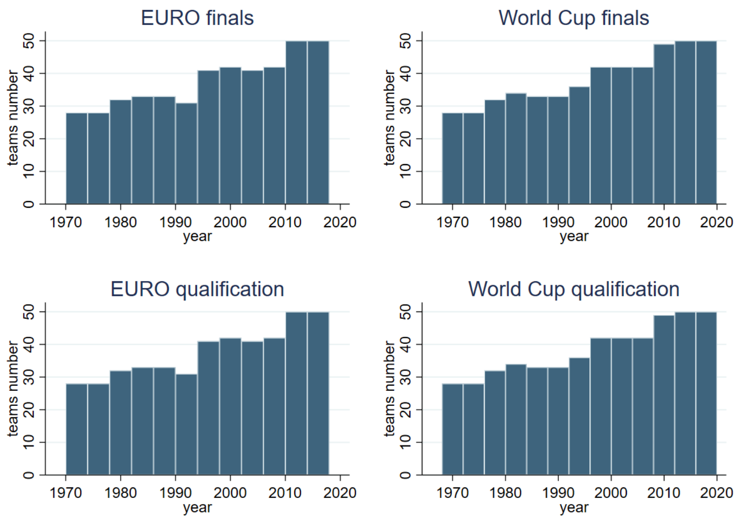

Figure 1.C.1: Number of teams in the sample, by year and tournament
Notes: In Figure 1.C.1, we plot the evolution of the number of teams participating to the EUROs (on the left) and to the World Cup (on the right). The equivalent number of teams in the qualification and final stages are a result of our unilateral panel construction, where we avoid teams dropping out to maintain balance and prevent out-selection issues.

stage, whereas virtually no limitations exist for the qualification matches, leaving eligibility criteria aside [43]. The limit of 22 players per squad was increased by 1 in the 2002 World Cup and EUROs 2004.

[43] The detailed regulations for the 2018 World Cup can be found at this site: https://www.uefa.com/MultimediaFiles/Download/Regulations/ uefaorg/Regulations/ 01/87/54/21/1875421_DOWNLOAD.pdf

1.D Additional tables

1.D.1 First-stage regressions

Table 1.D.1: Unilateral framework, benchmark, first-stage regressions

	First stage: Dependent variable: team's diversity			
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
IV				
IV, 18y lag	0.453***	0.453***	0.508***	0.331***
	(0.101)	(0.101)	(0.122)	(0.096)
Stand. dev. appearances		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Control variables				
Log of GDP/capita			-0.299**	-0.129
			(0.117)	(0.128)
Population (mln)			-0.015	
			(0.011)	
Log immig. stocks, 18y lag				-0.060***
				(0.017)
Observations	1900	1900	1900	1676
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	20.34	20.31	17.47	11.83
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Notes: First stage for the baseline estimates of the unilateral framework, Table 1.3. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) /years 1978–2018 (in Column 4). Dependent variable in the second stage: changes in the Elo score of the national team (end vs. beginning of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.2: Bilateral framework, benchmark, first-stage regressions

	First stage: Dependent variable: bilateral diversity				
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
Instrumental variable					
IV, home vs. away	0.451***	0.393***	0.454***	0.295***	0.295***
	(0.080)	(0.079)	(0.080)	(0.077)	(0.078)
Control variables					
Log of GDP/capita, home		-0.260**	-0.247**	-0.056	-0.056
		(0.086)	(0.085)	(0.103)	(0.103)
Log of GDP/capita, away		0.312***	0.292**	0.150	0.150
		(0.091)	(0.091)	(0.110)	(0.110)
Stand. dev. appearances, away		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Stand. dev. appearances, home		0.001***	0.001***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
Population (mln), home			-0.005***		
			(0.001)		
Population (mln), away			0.005***		
			(0.001)		
Log immig. stocks, 18y lag, home				-0.057**	-0.057**
				(0.019)	(0.019)
Log immig. stocks, 18y lag, away				0.039**	0.039**
				(0.020)	(0.020)
Observations	3877	3877	3877	3568	3568
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	31.46	24.52	32.29	14.48	14.49
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: First stage for the baseline estimates of the bilateral framework (match level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in columns 4–5). Dependent variable in the second stage: goal difference. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–5 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.3: Unilateral framework, alternative measure of rating, first-stage regressions

	First stage: Dependent variable: team's diversity			
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
IV				
IV, 18y lag	0.453***	0.508***	0.508***	0.331***
	(0.101)	(0.122)	(0.122)	(0.096)
Control variables				
Log of GDP/capita		-0.299**	-0.299**	-0.129
		(0.117)	(0.117)	(0.128)
Population (mln)		-0.015	-0.015	
		(0.011)	(0.011)	
Stand. dev. appearances		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Log immig. stocks, 18y lag				-0.060***
				(0.017)
Observations	1900	1900	1900	1676
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	20.34	17.47	17.47	11.83
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Notes: First stage for the estimates of the unilateral framework, Table 1.4. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in Column 4). Dependent variable in the second stage: Elo score levels of the national team (end of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.4: Unilateral framework, opponent's strength and diversity, first-stage regressions

	First stage: Dependent variable: team's diversity				
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
IV					
IV, 18y lag	0.453***	0.498***	0.496***	0.311**	0.308**
	(0.101)	(0.121)	(0.121)	(0.097)	(0.097)
Control variables					
Log of GDP/capita		-0.300**	-0.292**	-0.123	-0.120
		(0.116)	(0.115)	(0.127)	(0.126)
Population (mln)		-0.015	-0.015		
		(0.011)	(0.011)		
Adversary's diversity		0.046**			0.022
		(0.021)			(0.022)
Adversary's strength			0.001***	0.001***	0.001***
			(0.000)	(0.000)	(0.000)
Stand. dev. appearances			0.000	0.001	0.001
			(0.000)	(0.000)	(0.000)
Log immig. stocks, 18y lag				-0.063***	-0.064***
				(0.017)	(0.017)
Observations	1900	1900	1900	1676	1676
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	20.34	16.93	16.72	10.27	10.05
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes

Notes: First stage for the estimates of the unilateral framework, Table 1.6. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in Column 4). Dependent variable in the second stage: changes in the Elo score of the national team (end vs. beginning of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.5: Unilateral framework, further results, first-stage regressions

	First stage: Dependent variable: team's diversity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV	IV	IV	IV	IV	IV	IV
IV							
IV, 18y lag	0.453***	0.498***	0.496***	0.311**	1.095**		
	(0.101)	(0.121)	(0.121)	(0.097)	(0.348)		
Log of GDP/capita		-0.300**	-0.292**	-0.123	-1.116***	-0.214*	-0.147
		(0.116)	(0.115)	(0.127)	(0.329)	(0.120)	(0.128)
Population (mln)		-0.015	-0.015		-0.025	-0.025**	-0.033**
		(0.011)	(0.011)		(0.030)	(0.012)	(0.013)
Adversary's diversity		0.046**					
		(0.021)					
Adversary's strength			0.001***	0.001***			
			(0.000)	(0.000)			
Control variables							
Stand. dev. appearances			0.000	0.001	0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Log immig. stocks, 18y lag				-0.063***			
				(0.017)			
L.IV, 18y lag						0.667***	
						(0.147)	
L2.IV, 18y lag							0.905***
							(0.184)
Observations	1900	1900	1900	1676	1900	1784	1670
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	20.34	16.93	16.72	10.27	9.88	20.54	24.29
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: First stage for the estimates of the unilateral framework, Table 1.7. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3 and 5) / years 1978–2018 (in Column 4). Dependent variable in the second stage: goal difference for columns 1–4 and 6, its hyperbolic sine transformation in Column 5 and the goals scored by the home team in Column 7. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.6: Unilateral framework, coach quality, first-stage regressions

	First stage: Dependent variable: team's diversity			
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
IV, 18y lag	0.459***	0.459***	0.515***	0.338***
	(0.101)	(0.101)	(0.123)	(0.097)
Control variables				
Coach age	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Foreign_coach==1	-0.030	-0.031	-0.017	-0.040
	(0.054)	(0.053)	(0.053)	(0.057)
Stand. dev. appearances		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Log of GDP/capita			-0.293**	-0.114
			(0.117)	(0.129)
Population (mln)			-0.015	
			(0.011)	
Log immig. stocks, 18y lag				-0.060***
				(0.017)
Observations	1900	1900	1900	1676
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	20.53	20.51	17.57	12.12
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Notes: First stage for the estimates of the Unilateral framework, Table 1.8. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in Column 4). Dependent variable in the second stage: changes in the Elo score of the national team (end vs. beginning of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.7: Unilateral framework, accounting for intercontinental matches, first-stage regressions

	First stage: dependent variable: team's diversity			
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
IV				
IV, 18y lag	0.453***	0.453***	0.508***	0.331***
	(0.101)	(0.101)	(0.122)	(0.096)
Stand. dev. appearances		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Control variables				
Log of GDP/capita			-0.299**	-0.129
			(0.117)	(0.128)
Population (mln)			-0.015	
			(0.011)	
Log immig. stocks, 18y lag				-0.060***
				(0.017)
Observations	1900	1900	1900	1676
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	20.34	20.31	17.47	11.83
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Notes: First stage for the estimates of the Unilateral framework, Table 1.9. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in Column 4). Dependent variable in the second stage: changes in the Elo score of the national team (end vs. beginning of the championship stage), as from the web source elorating.net. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.8: Bilateral framework, controlling for initial strength, first-stage regressions

	First stage: Dependent variable: bilateral diversity				
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
Instrumental variable					
IV, home vs. away	0.454***	0.398***	0.462***	0.301***	0.302***
	(0.080)	(0.079)	(0.080)	(0.077)	(0.077)
Control variables					
Initial Elo score, home	-0.000	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Initial Elo score, away	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of GDP/capita, home		-0.268**	-0.256**	-0.076	-0.076
		(0.086)	(0.086)	(0.101)	(0.101)
Log of GDP/capita, away		0.314***	0.294**	0.157	0.156
		(0.091)	(0.091)	(0.109)	(0.109)
Stand. dev. appearances, away		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Stand. dev. appearances, home		0.002***	0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
Population (mln), home			-0.005***		
			(0.001)		
Population (mln), away			0.005***		
			(0.001)		
Log immig. stocks, 18y lag, home				-0.049**	-0.049**
				(0.018)	(0.018)
Log immig. stocks, 18y lag, away				0.037*	0.037*
				(0.019)	(0.019)
Observations	3877	3877	3877	3568	3568
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	31.87	25.31	33.49	15.26	15.27
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: First stage for the estimates of the bilateral framework, Table 1.10. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970—2018 (columns 1–3 and 5) / years 1978–2018 (in Column 4) first year available for the instrument to 2018 (columns 6 and 7). Dependent variable in the second stage: changes in the Elo score of the national team (end vs. beginning of the championship stage). In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–4 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, corrected for arbitrary autocorrelation of degree 1. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * p < .10, *** p < .05, *** p < .001.

Table 1.D.9: Bilateral framework, further results, first-stage regressions

	Dependent variable in second stage: goal difference				hyperbolic sine	Home score	Goal difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV: Diversity, appearance	**IV:** Diversity, SW	**IV:** 20 years lag	**IV:** 22 years lag	**IV:**Goal difference, hyperbolic sine	**IV:**Outcome: home score	**IV:**Diversity, home vs. away
Instrumental variable							
IV, home vs. away	0.380***	0.402***			0.454***	0.454***	
	(0.072)	(0.084)			(0.080)	(0.080)	
Stand. dev. appearances, away	-0.001***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stand. dev. appearances, home	0.001***	0.002***	0.001***	0.001***	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population (mln), home	-0.002**	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population (mln), away	0.003**	0.005***	0.006***	0.006***	0.005***	0.005***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Control variables							
Log of GDP/capita, home	-0.312***	-0.348***	-0.223**	-0.188**	-0.247**	-0.247**	-0.391***
	(0.088)	(0.096)	(0.084)	(0.085)	(0.085)	(0.085)	(0.078)
Log of GDP/capita, away	0.269**	0.363***	0.278**	0.246**	0.292**	0.292**	0.005
	(0.092)	(0.103)	(0.089)	(0.090)	(0.091)	(0.091)	(0.104)
Observations	3877	3877	3762	3643	3877	3877	3877
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	28.13	22.76	40.42	47.09	32.29	32.29	15.47
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute appearances	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: First stage for the estimates of the bilateral framework (match level), Table 1.11. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–2, 5–7) / the first year available for the instrument to 2018 (in columns 3–4). Dependent variable in the second stage: goal difference for columns 1–4 and 6, its hyperbolic sine transformation in Column 5 and the goals scored by the home team in Column 7. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–7 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.D.10: Bilateral framework, controlling for coach information, first-stage regressions

	First stage: Dependent variable: bilateral diversity				
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
Instrumental variable					
IV, home vs. away	0.458***	0.400***	0.463***	0.305***	0.305***
	(0.082)	(0.081)	(0.082)	(0.080)	(0.080)
Coach age, home	-0.004*	-0.004**	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Coach age, away	0.004*	0.005**	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Control variables					
Foreign coach, home	-0.047	-0.053	-0.045	-0.083**	-0.083**
	(0.038)	(0.038)	(0.038)	(0.039)	(0.039)
Foreign coach, away	0.012	0.009	0.000	0.038	0.038
	(0.036)	(0.036)	(0.036)	(0.039)	(0.039)
Log of GDP/capita, home		-0.255**	-0.242**	-0.052	-0.052
		(0.086)	(0.086)	(0.104)	(0.104)
Log of GDP/capita, away		0.326***	0.306***	0.160	0.159
		(0.093)	(0.092)	(0.113)	(0.113)
Stand. dev. appearances, away		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Stand. dev. appearances, home		0.002***	0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
Population (mln), home			-0.005***		
			(0.001)		
Population (mln), away			0.006***		
			(0.001)		
Log immig. stocks, 18y lag, home				-0.057**	-0.057**
				(0.019)	(0.019)
Log immig. stocks, 18y lag, away				0.041**	0.041**
				(0.020)	(0.020)
Observations	3873	3873	3873	3568	3568
Kleibergen-Paap LM test	0.00	0.00	0.00	0.00	0.00
Kleibergen-Paap F test	30.97	24.22	32.21	14.64	14.65
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances		Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: First stage for the baseline estimates of the bilateral framework (match level), Table 1.13. Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in columns 4–5). Dependent variable in the second stage: goal difference. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–5 display IV first-stage results, with heteroskedastic robust standard errors in parentheses, clustered at team pair level. For each IV specification, we present the p-value from the Kleibergen-Paap Lagrange Multiplier test for the instrument relevance, as well as the F-statistics from Kleibergen-Paap F test for weak instruments. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

1.E

Other tables

We report the full table of results for the control function approach reported in the Sensitivity checks section for the bilateral estimations (Table 1.12 reports the average partial effects).

Table 1.E.1: Bilateral framework, goals for

	Dependent variable: home team's goals scored				
	(1) **IV:**Poisson, control function	(2) **IV:**Poisson, control function	(3) **IV:**Poisson, control function	(4) **IV:**Poisson, control function	(5) **IV:**Poisson, control function
Diversity, away	-0.139	-0.253	-0.242*	-0.411*	-0.411*
	(0.139)	(0.161)	(0.143)	(0.225)	(0.226)
RES_FEd	0.115	0.241	0.231	0.390*	0.389*
	(0.139)	(0.162)	(0.145)	(0.226)	(0.227)
Diversity, home	0.281*	0.333*	0.350**	0.389	0.386
	(0.156)	(0.181)	(0.161)	(0.296)	(0.298)
RES_FEo	-0.255	-0.325*	-0.346**	-0.383	-0.381
	(0.156)	(0.180)	(0.161)	(0.296)	(0.298)
Log of GDP/capita, home		0.245*	0.259*	0.143	0.142
		(0.145)	(0.140)	(0.162)	(0.163)
Log of GDP/capita, away		-0.427***	-0.418***	-0.279**	-0.276*
		(0.129)	(0.121)	(0.140)	(0.141)
Stand. dev. appearances, away		-0.003***	-0.003***	-0.003***	-0.003***
		(0.000)	(0.000)	(0.001)	(0.001)
Stand. dev. appearances, home		0.002***	0.002***	0.002**	0.002**
		(0.000)	(0.000)	(0.001)	(0.001)
Population (mln), home			-0.000		
			(0.001)		
Population (mln), away			-0.000		
			(0.002)		
Log immig. stocks, 18y lag, home				0.041	0.041
				(0.034)	(0.034)
Log immig. stocks, 18y lag, away				-0.068**	-0.068**
				(0.027)	(0.028)
Observations	3877	3877	3877	3568	3568
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances	Yes	Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: Coefficients table, relative to Table 1.12's home score results. Estimates for the bilateral framework (match level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in columns 4–5). Dependent variable: home team's number of goals scored in the top sub-table, Away team's number of goals scored in the top sub-table. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–5 display results from a Poisson, control-function regression, with bootstrapped (2000 reps) standard errors in parentheses, clustered at team pair level. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.E.2: Bilateral framework, goals against

	Dependent variable: away team's goals scored				
	(1) **IV:**Poisson, Control function	(2) **IV:**Poisson, control function	(3) **IV:**Poisson, control function	(4) **IV:**Poisson, control function	(5) **IV:**Poisson, control function
Diversity, away	0.370**	0.406**	0.331**	0.456*	0.463*
	(0.161)	(0.181)	(0.159)	(0.261)	(0.262)
RES_FEd	-0.363**	-0.417**	-0.341**	-0.463*	-0.469*
	(0.161)	(0.181)	(0.160)	(0.263)	(0.264)
Diversity, home	-0.169	-0.191	-0.203	-0.452	-0.439
	(0.171)	(0.202)	(0.179)	(0.351)	(0.355)
RES_FEo	0.156	0.199	0.212	0.458	0.447
	(0.172)	(0.203)	(0.181)	(0.351)	(0.355)
Log of GDP/capita, home		-0.092	-0.103	0.020	0.027
		(0.162)	(0.152)	(0.191)	(0.193)
Log of GDP/capita, away		0.343**	0.298*	0.173	0.185
		(0.163)	(0.156)	(0.171)	(0.172)
Stand. dev. appearances, away		0.003***	0.003***	0.003***	0.003***
		(0.000)	(0.000)	(0.001)	(0.001)
Stand. dev. appearances, home		-0.003***	-0.003***	-0.002***	-0.002***
		(0.001)	(0.000)	(0.001)	(0.001)
Log immig. stocks, 18y lag, home				-0.081**	-0.080**
				(0.038)	(0.038)
Log immig. stocks, 18y lag, away				0.061*	0.060*
				(0.034)	(0.034)
Observations	3877	3877	3877	3568	3568
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances	Yes	Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: Coefficients table, relative to Table 1.12's away score results. Estimates for the bilateral framework (match level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in columns 4–5). Dependent variable: home team's number of goals scored in the top sub-table, Away team's number of goals scored in the top sub-table. Columns 1–5 display results from a Poisson, control-function regression, with bootstrapped (2000 reps) standard errors in parentheses, clustered at team pair level. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.E.3: Bilateral framework, first stage, for home team diversity

	Dependent variable: home team's goals scored				
	(1) **IV:**Poisson, control function	(2) **IV:**Poisson, control function	(3) **IV:**Poisson, control function	(4) **IV:**Poisson, control function	(5) **IV:**Poisson, control function
IV, away	-0.009	-0.000	-0.007	0.006	0.005
	(0.058)	(0.060)	(0.060)	(0.063)	(0.062)
IV, home	0.413***	0.364***	0.418***	0.270***	0.267***
	(0.070)	(0.067)	(0.070)	(0.068)	(0.065)
Log of GDP/capita, home		-0.411***	-0.391***	-0.225**	-0.227**
		(0.079)	(0.081)	(0.091)	(0.089)
Log of GDP/capita, away		0.009	0.005	-0.040	-0.044
		(0.100)	(0.101)	(0.115)	(0.119)
Stand. dev. appearances, away		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Stand. dev. appearances, home		0.001**	0.001**	0.001**	0.001**
		(0.000)	(0.000)	(0.000)	(0.000)
Population (mln), home			-0.006***		
			(0.001)		
Population (mln), away			0.001		
			(0.002)		
Log immig. stocks, 18y lag, home				-0.064***	-0.064***
				(0.018)	(0.018)
Log immig. stocks, 18y lag, away				0.004	0.003
				(0.021)	(0.020)
Observations	3877	3877	3877	3568	3568
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances	Yes	Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: Coefficients table, relative to Table 1.12's home score results. First stage on estimates for the bilateral framework (match level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in columns 4–5). Dependent variable: home team's number of goals scored in the top sub-table, Away team's number of goals scored in the top sub-table. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–5 display linear first-stage results from a second-stage Poisson, with a control-function method, and bootstrapped (2000 reps) standard errors in parentheses, clustered at team pair level. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.E.4: Bilateral framework, first stage, for away team diversity

	Dependent variable: home team's goals scored				
	(1)	(2)	(3)	(4)	(5)
	IV: Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function	**IV:**Poisson, control function
IV, away	0.473***	0.418***	0.477***	0.330***	0.329***
	(0.072)	(0.069)	(0.071)	(0.069)	(0.067)
IV, home	-0.008	-0.005	-0.008	0.003	0.001
	(0.055)	(0.056)	(0.056)	(0.061)	(0.061)
Log of GDP/capita, home		-0.055	-0.051	-0.147	-0.150
		(0.096)	(0.096)	(0.111)	(0.109)
Log of GDP/capita, away		-0.419***	-0.394***	-0.244**	-0.248**
		(0.079)	(0.080)	(0.091)	(0.090)
Stand. dev. appearances, away		0.001**	0.000*	0.001**	0.001**
		(0.000)	(0.000)	(0.000)	(0.000)
Stand. dev. appearances, home		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Population (mln), home			0.000		
			(0.001)		
Population (mln), away			-0.006***		
			(0.001)		
Log immig. stocks, 18y lag, home				0.015	0.015
				(0.019)	(0.019)
Log immig. stocks, 18y lag, away				-0.050**	-0.051**
				(0.017)	(0.018)
Observations	3877	3877	3877	3568	3568
Team FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes
Minute appearances	Yes	Yes	Yes	Yes	Yes
Geo-political controls					Yes

Notes: Coefficients table, relative to Table 1.12's away score results. First stage on estimates for the bilateral framework (match level). Estimation sample: football national teams from the UEFA affiliation, performing in World Cup and EUROs in the years 1970–2018 (for columns 1–3) / years 1978–2018 (in columns 4–5). Dependent variable: home team's number of goals scored in the top sub-table, Away team's number of goals scored in the top sub-table. In all regressions, we include team and year fixed effects, as well as a stage dummy. Columns 1–5 display linear first-stage results from a second-stage Poisson, with a control-function method, and bootstrapped (2000 reps) standard errors in parentheses, clustered at team pair level. Stars correspond to the following p-values: * $p < .10$, *** $p < .05$, *** $p < .001$.

Table 1.E.5: Placebo, baseline estimations for the sake of comparison

	Dependent variable: change in rating of national football team (Elo score)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Variable of interest								
Diversity	2.943**	2.626**	2.807**	2.654*	22.417**	19.178*	23.652**	36.505*
	(1.136)	(1.156)	(1.129)	(1.395)	(11.128)	(10.479)	(11.655)	(20.356)
Population (mln)	0.193	0.293	0.322	0.241	-0.010	0.125	0.140	-0.267
	(0.245)	(0.226)	(0.208)	(0.310)	(0.413)	(0.407)	(0.414)	(0.692)
Stand. dev. appearances		0.276***	0.277***	0.310***		0.292***	0.293***	0.316***
		(0.023)	(0.023)	(0.028)		(0.026)	(0.027)	(0.033)
Log of GDP/capita			8.814	9.903			18.034**	17.371*
			(6.494)	(7.609)			(8.061)	(9.464)
Log immig. stocks, 18y lag				-0.476				1.599
				(1.369)				(1.944)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					18.61	18.53	16.66	7.34
Kleibergen-Paap F test					20.74	20.60	17.47	7.69
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 1.E.6: Placebo analysis: performances in athletics (all medals) and ancestral diversity

	Dependent variable: total medals in athletics championship							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Variable of interest								
Diversity	0.046	0.046	0.044	0.017	-0.151	-0.152	-0.213	-1.112
	(0.155)	(0.155)	(0.154)	(0.157)	(0.438)	(0.436)	(0.500)	(0.925)
Population (mln)	0.170*	0.170*	0.169*	0.226*	0.172***	0.172***	0.172***	0.243***
	(0.099)	(0.099)	(0.099)	(0.114)	(0.031)	(0.031)	(0.031)	(0.048)
Stand. dev. appearances		0.000	0.000	-0.001		0.000	0.000	-0.000
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Log of GDP/capita			-0.136	-0.095			-0.244	-0.333
			(0.540)	(0.843)			(0.358)	(0.452)
Log immig. stocks, 18y lag				0.001				-0.068
				(0.140)				(0.095)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					18.61	18.53	16.66	7.34
Kleibergen-Paap F test					20.74	20.60	17.47	7.69
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 1.E.7: Placebo analysis: performances in athletics (gold medals) and ancestral diversity

	Dependent variable: gold medals in athletics championship							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Variable of interest								
Diversity	0.035	0.036	0.033	0.028	0.074	0.076	0.050	0.004
	(0.059)	(0.060)	(0.058)	(0.061)	(0.185)	(0.185)	(0.208)	(0.345)
Population (mln)	0.058	0.058	0.057	0.076*	0.057***	0.057***	0.057***	0.076***
	(0.036)	(0.036)	(0.036)	(0.042)	(0.012)	(0.012)	(0.012)	(0.017)
Stand. dev. appearances		-0.000	-0.000	-0.000		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)
Log of GDP/capita			-0.112	-0.046			-0.105	-0.051
			(0.239)	(0.387)			(0.159)	(0.199)
Log immig. stocks, 18y lag				-0.012				-0.014
				(0.063)				(0.043)
Observations	1900	1900	1900	1676	1900	1900	1900	1676
Kleibergen-Paap LM test					18.61	18.53	16.66	7.34
Kleibergen-Paap F test					20.74	20.60	17.47	7.69
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

1.F Additional graphs and tables

To complete figures 1.1 and 1.3, we present the same cross-sectional maps for the final stages.

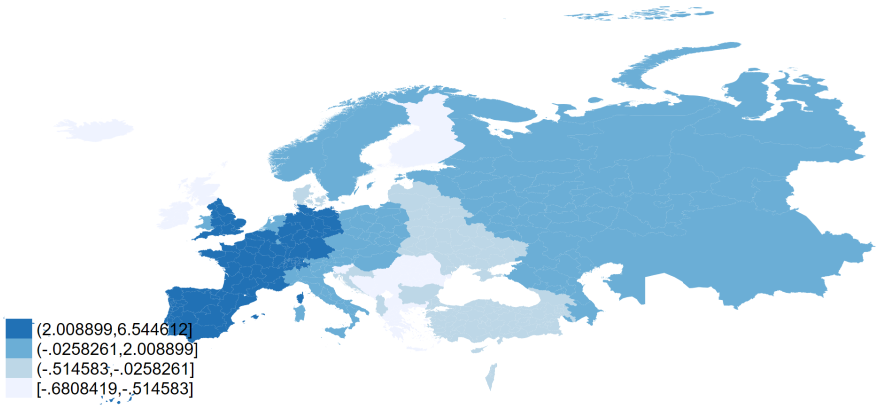

Figure 1.F.1: Cross-country diversity: descriptive example, EURO 2016, final stage
We present this graph to complete Figure 1.1. This snapshot represents diversity indices for the final stages of 2016 EURO games. As for Figure 1.1, the graph broadly presents higher levels of diversity on the Western side of the continent.

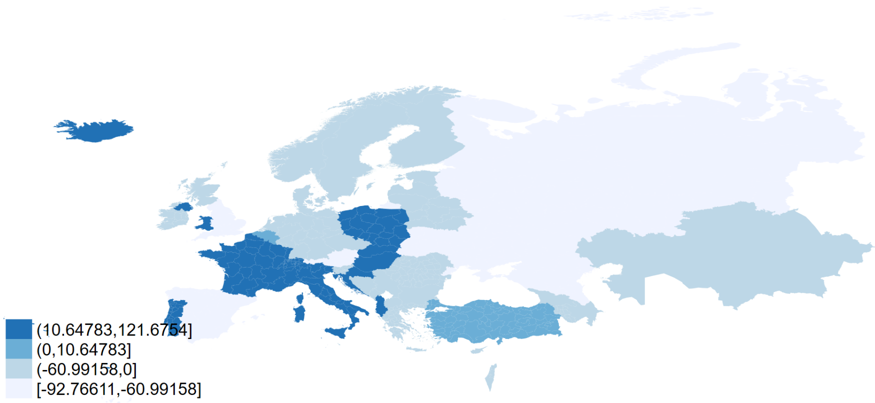

Figure 1.F.2: Cross-country changes in Elo score: descriptive example, EUROs 2016, final stage
We present this graph to complete Figure 1.3. This snapshot represents Elo score changes for the final stages of 2016 EURO games. The tournament champion is Portugal, which won a final match against France, the hosting nation.

Table 1.F.1: List of countries in the sample, by year in the unilateral sample. Three-letter codes follow the ISO three-letters specification.

ALB	1972 1974 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
ARM	1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
AUT	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
AZE	1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
BEL	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
BGR	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
BIH	2010 2012 2014 2016 2018
BLR	1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
CHE	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
CSK	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994
CYP	1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
CZE	2012 2014 2016 2018
DDR	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990
DEU	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
DNK	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
ENG	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
ESP	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
EST	1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
FIN	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
FRA	1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
GEO	1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
GRC	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
HRV	2010 2012 2014 2016 2018
HUN	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
IRL	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
ISL	1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
ISR	1970 1982 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
ITA	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
KAZ	2006 2008 2010 2012 2014 2016 2018
LTU	1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
LUX	1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
LVA	1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
MDA	1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
MKD	2010 2012 2014 2016 2018
MLT	1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
MNE	2010 2012 2014 2016 2018
NIR	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
NLD	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
NOR	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
POL	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
PRT	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
ROU	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
RUS	1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
SCT	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
SMR	1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
SRB	1998 2000 2002 2010 2012 2014 2016 2018
SUN	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990
SVK	2010 2012 2014 2016 2018
SVN	2010 2012 2014 2016 2018
SWE	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
TUR	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
UKR	1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
WLS	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016 2018
YUG	1970 1972 1974 1976 1978 1980 1982 1984 1986 1988 1990

List of national teams by year in the Unilateral sample. 3 letter codes follow a ISO 3-letters specification.

List of variables

Table 1.F.2: Description of variables, unilateral specifications

Variable name	Variable description	Variable source
Performance measures		
Elo score	Elo score or the team at the end of the stage	Retrieved from eloratings.net
Elo score, computed	Elo score or the team at the end of the stage	Own computation from match level data
Diversity measures		
Diversity	Benchmark Diversity measure, genetic distances are based on dominant populations	Source for surname predictions: forebears.io. Source for genetic distance measures: Spolaore and Wacziarg, 2009
Diversity, apperance	Diversity alternative measure, weighted by minute appearances	As above
Diversity, SW.	Diversity alternative measure, based on weighted genetic distances	As above
Team-level variables		
Adversary's diversity	Average diversity level of the teams faced	Own computation from match level data
Adversary's strength	Average Elo score level of the teams faced, measured at the beginning of the stage	As above
Foreign coach	Dummy =1 if the team's manager is foreign	Retrieved from squad-level data on worldfootball.net
Coach age	Age of coach (approximated), computed as year of championship minus year of birth	As above
Stand. dev. appearances	Player turnover as computed from the minute appearances	As above
Stand. dev. squad age	Standard deviation of team members' age	As above
Squad age	Average of team members' age	As above
Squad age, squared	Square of squad age.	As above
Squad size	Number of players in the squad (fixed in the final stages)	As above
Macroeconomic variables		
Log immig. stocks, 18y lag	Log of the stocks of immigrants, lagged 18 years	World Development Indicators (WDI), International migrant stock, total (SM.POP.TOTL), linear interpolation was conducted on the 5-year-interval data. Complemented by the World Bank's Bilateral Migration Matrix, Özden et al., 2011
Log of GDP/capita	Log of per capita GDP	National Accounts Section of the United Nations Statistics Division: National Accounts Main Aggregates Database
Population (mln)	Country population size (millions of units)	WDI, SP.POP.TOTL total population; Head et al., 2010
IV		
IV, 18y lag	Instrumental variable: historical diversity level, 18 years' lag (benchmark lag)	Cline Center for Advanced Social Research. Complemented with the World Bank's bilateral migration matrix (Özden et al., 2011)

Notes: Description of variables and their respective sources employed in the unilateral estimations.

Table 1.F.3: Description of variables, bilateral specifications

Variable name	Variable description	Variable source
Performance measures		
Goal difference	Goals of team i *home* - Goals of team j. *away*	Mart Jürisoo
Goal difference, hyperbolic sine	Hyperbolic sine transformation of *Goal difference*	*see Goal difference*
Diversity measures		
Bilateral diversity	Diversity score of team i *home* - Diversity score of team j *away*. Benchmark measure, genetic distances are based on dominant populations	Surname predictions: forebears.io. Genetic distance measures: Spolaore and Wacziarg, 2009
Bilateral diversity, appearance	Diversity score of team i *home* - Diversity score of team j *away*. Alternative measure, weighted by minute appearances	As above
Bilateral diversity, SW	Diversity score of team i *home* - Diversity score of team j *away*. Alternative measure, based on weighted genetic distances.	As above
Diversity, home (Diversity, away)	Diversity score of team i *home* (team j *away*)	As above
Team-level variables		
Stand. dev. squad age, home (Stand. dev. squad age, away)	Standard deviation of team i *home* (team j *away*) members' age	Constructed from squad-level data on worldfootball.net
Squad age, home (Squad age, away)	Average of team i *home* (team j *away*) members' age	As above
Squad age, squared, home (Squad age, squared, away)	Square of squad age, home (*away*)	As above
Stand. dev. appearances, home (Stand. dev. appearances, away)	Player turnover for team i *home* (team j *away*), as computed from the minute appearances	As above
Foreign coach, home (Foreign coach, away)	Dummy =1 if the team i *home* (team j *away*)'s manager is foreign	As above
Coach age, home (Coach age, away)	Age of team i *home* (team j *away*)'s coach (approximated), computed as year of championship minus year of birth	As above
Macroeconomic variables		
Population (mln), home (Population (mln), away)	Team i *home* (team j *away*)'s country population size (millions of units)	WDI, SP.POP.TOTL total population; Head et al., 2010
Log of GDP/capita, home (log of GDP/capita, away)	Log of per capita GDP for team i *home* (team j *away*)'s country	UN Statistics Division: National Accounts Main Aggregates Database
Log immig. stocks, 18y lag, home (Log immig. stocks, 18y lag, away)	Log of the stocks of immigrants for team i *home* (team j *away*)'s country, lagged 18 years	WDI, International migrant stock (see Unilateral table for details.) Complemented with (Özden et al., 2011)
Adversary's strength, home (Adversary's strength, away)	Average Elo score level of the teams faced, measured at the beginning of the stage	Own computation from match-level data
Contiguity	Dummy =1 if the team i *home* and j *away*) share/ have shared historically a border	Spolaore and Wacziarg, 2009
Same nation	Dummy =1 if the team i *home* and j *away*) are/ have been historically part of the same nation	As above
Common language	Dummy =1 if the team i *home* and j *away*) share/ have shared historically an official language	As above

Notes: Description of variables and their respective sources employed in the bilateral estimations.

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Chapter 2

Migrants' crisis in the local news: evidence from the French-Italian border

Abstract

This paper investigates the impact of local exposure to the migrant crisis on the local news market. Exploiting a narrow geographical setting, it explores a policy dating from June 2015, whereby French authorities introduced militarized controls at the Italian frontier. With the border controls in place, groups of migrants and asylum seekers who had planned to cross the border irregularly were pushed back to the Italian lands. With rejected migrants clustering at the border, natives residing along the Italian region were unevenly exposed to their settlement. Taking advantage of this unequal treatment as a natural experiment, this study uses novel data collected on the text and on the number of local news items for the border areas of Liguria, Italy, between 2011 and 2019. It documents that the backlog of migrants in the Italian border area was substantially mediatized: coverage of migration rose most in the most exposed municipalities. Conversely, anti-immigrant discourse in the news grew more in areas least directly in contact with the border. Exploring further this framing dimension, the bias effect turns out to be shaped by readers' demand and to be closely associated with local news penetration. Finally, this study documents that anti-immigrant slant and voting preferences share a similar direction, while a related broad pattern also appears in hate-crime records.

2.1 Introduction

Over the past decade, Europe has experienced an unprecedented rise in undocumented migration, with a remarkable peak between 2014 and 2016. Italy, in particular, experienced a surge in arrivals of migrants and asylum seekers, departing from the Libyan coasts on the so-called "Central Mediterranean Route." In 2014 and 2015 arrivals along this route reached 170 thousand and 150 thousand individuals, respectively (European Border and Coast Guard Agency, henceforth "Frontex"). These events inflamed the public debate both nationally and at the EU level, leading to viral attention in the media discourse (Chouliaraki et al., 2017).[44] Several scholars attributed the widespread success of populist, anti-immigrant parties in various EU countries to the direct exposure of natives to the presence of, or proximity to, migrant inflows (Campo et al., 2021; Edo et al., 2019; Otto & Steinhardt, 2014). Moreover, the role of media has been identified as an important mechanism of diffusion and persuasion of attitudes and expressed political preferences (Bratti et al., 2020; DellaVigna & Kaplan, 2007; Djourelova, 2020; Gentzkow, 2006). Despite this, media companies do not exogenously select the message to spread. When exploring the news market in particular, competition and readership beliefs are key factors in determining the supply of news information (Mullainathan & Shleifer, 2005).

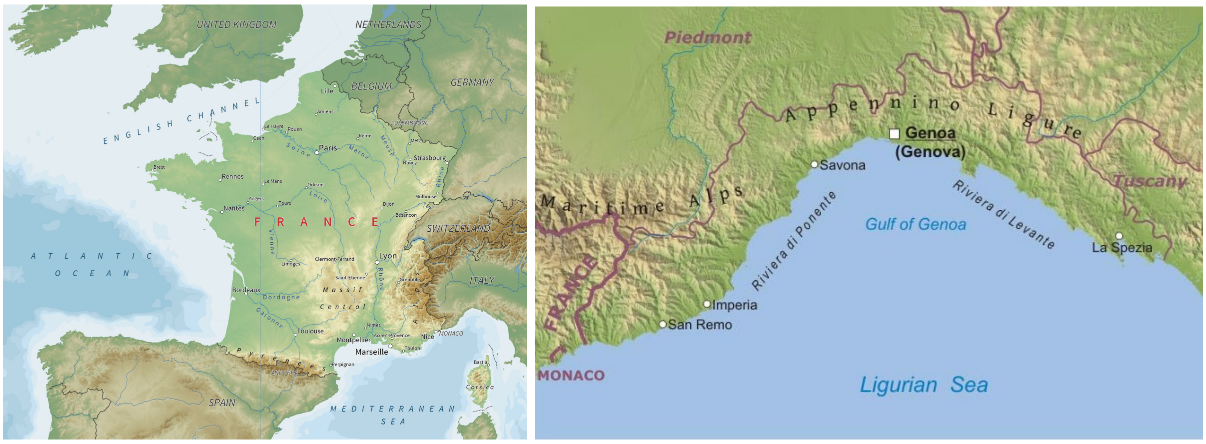
This study examines these news production mechanisms and investigates them along two dimensions. It first poses the question: *How do local shocks in the presence of backlogged migrants impact the local news market?* Second, *Which news patterns, if any, match the local political economy?* This research relies on an exogenous shock in the number of migrants at the Italian border to examine how local news outlets changed their output based on two choices: the volume and quality of discourse connected to migration.

The sudden shock of interest occurred in June 2015, when French local authorities systematically imposed militaristic border controls at the border with Italy. This policy aimed at and resulted in substantial push-backs of migrants to Italian lands, which, for morphological reasons, funnelled migrants predominantly to the coastal border into the town of Ventimiglia, Liguria (Italy). To better understand the geographic connection between France and Italy, see Figure 2.1.1. On the left, a physical map of France highlights how bondaries with Italy are shaped by the Alps. On the right, a physical map of Liguria outlines the geography of the region, showing how mountains make the coastal area more accessible.[45]

[44] For a comprehensive review of the refugee crisis, with a focus on the reception policies from EU members, one can refer to Dustmann et al., 2017.

[45] As a complement, an additional map realized by NGO La Cimade is reported in Figure A.1. This map helps visualizing the dynamics of the border push-backs.

Figure 2.1.1: Physical maps of France and Italy



Notes: On the left, a physical map of France. Source: Mapswire.com, https://mapswire.com/maps/france/. On the right, a physical map of Liguria. Source: Daniel Feher, https://www.freeworldmaps.net/europe/italy/images/liguria.jpg.

Before the policy of border restrictions, many migrants in dire circumstances in Italy had taken advantage of this gateway in an effort to travel to their eventual destinations in other European nations.[46]

This study is grounded in a localized methodology that takes into account the unique geography of the imposition of border restrictions and the overall migration patterns of the area. It focuses on the local government units of the coastal border region of Liguria, and specifically on the border province, Imperia, and its adjacent province, Savona. For the identification strategy being used, this is essential. In this setting, locals' exposure to the migrant settlements is inversely related with how far they must commute to get to the border, where the incidents occurred. Based on that, distance can be used as a proxy for how municipalities are exposed directly to the border events. To better track changes in local information demand, local news is the information channel of interest within this local dimension. Given that the internet is a widely used technology in the region, this study focuses on online news.[47] The analysis is based on a collection of about fifty thousand articles from the quasi-universe of local news in the study areas. Articles are selected if they contain specific keywords, that is the stemmed versions of the words "migrant," "immigrant," "foreigner," "non-EU citizen" (It., "extracomunitario") or "displaced person" (It., "profugo"). Then, using Google Trends, articles are geo-localized and combined to create a municipality-month-year panel dataset that spans the years 2011 to 2019.

[46] Other gateways included Bardonecchia, Como and Brennero (Capitani, 2018). Upon arrival in southern Italy, as described in Campo et al., 2021, migrants were subject to an allocation scheme created in 2014 to support the current receiving system of asylum petitions. Many intended to continue traveling, circumventing the bureaucratic process of status regularization in Italy (Capitani, 2018; Colombeau, 2020). For further information on how asylum seekers sorted in Europe, see also Aksoy and Poutvaara, 2021.

[47] In the sampled period, the region of interest had a higher percentage of people using the internet for e-mail and news than the Italian average (see Figure A.6 for internet usage rates over time in the region of interest, compared to all Italy).

The impact of the settlement of migrants on local news is examined along two lines: i) the coverage of migration and ii) the news' partisanship or "slant." These two important characteristics exist respectively as *agenda-setting* and *framing* in the taxonomy of the communication literature by Scheufele and Tewksbury, 2007. For the first dimension, the core outcome measure is a count of articles related to migration in the local news.[48] For the second dimension, this study builds upon the literature on measuring partisanship in the news (Gentzkow & Shapiro, 2010; Groseclose & Milyo, 2005; Taddy, 2013), as well as advances in supervised machine learning for text analysis, to build an indicator of language slant. Throughout the paper, media bias and slant are used interchangeably, in line with the definitions of Gentzkow et al., 2015 for media bias-" systematic differences in the mapping from facts to news reports [...] which tend to sway naive readers to the right or left on political issues" (page 3)-and of Gentzkow and Shapiro, 2010 for media slant-"the frequency with which newspapers use language that would tend to sway readers to the right or to the left on political issues" (page 36).[49]

Specifically, this paper uses an algorithm to determine whether a local news article has anti-immigrant terminology by comparing the similarity of its text with that of anti-immigrant versus more positively leaning national news outlets. This procedure builds upon the seminal index of Groseclose and Milyo, 2005, who compared congressional citations of US think tanks to citations of think tanks in newspapers, and the more sophisticated techniques of Gentzkow and Shapiro, 2010 and Taddy, 2013, which detected slant using the entire language in the Congress and in the news. In this paper, the local news slant is predicted using a body of national and regional newspapers with or without a known anti-immigrant orientation. This body constitutes the reference against which to compare the text in the local news pool. News articles in this pre-labeled dataset are carefully selected. Lacking comprehensive data on the text of the politicians, this enables the adoption of comparable machine learning algorithms by relying on rich text contents. This paper's findings can be summarized as follows. The backlog of migrants resulted led to a notable prominence of migration in the local media discourse. It caused a differential increase in news coverage that declines by 6% for every additional 10 minutes of commute time from the border. The share of anti-immigrant news, however, is observed to grow more in the municipalities further away after the migrants' forced settlement at the border. For each additional 10 minutes increase in commute time from the border, anti-immigrant slant increases by 0.22 standard deviations, after the border closure. Further evidence proposes a set of mechanisms

[48] A second, less central measure is also presented: an index of news importance. This is taken from the patents literature (Kelly et al., 2021), and enables the capture of a perceptive description of text evolution over time. An *important* article is *impactful* (its text resembles future articles) and *novel* (its text is dissimilar from that in previous articles).

[49] Importantly, the notion of agenda-setting can also be understood as a form of bias (Prat & Strömberg, 2013). This paper opts for the terminology of Gentzkow et al., 2015 and Gentzkow and Shapiro, 2010 and treats media bias and slant as substitutes.

to rationalize this finding.

First, the role of the demand for news is found to be crucial. This finding emerges when comparing the results by giving more or less weight to the distribution of local news readership, which is proxied with Google Trends information. Additionally, local news is found to gain market against national news in the areas where slant grew more. According to the framework of Mullainathan and Shleifer, 2005, readers have biased beliefs and media firms can accommodate these beliefs by slanting the information towards them. Where readers' opinions are more heterogeneous, their demand pushes slant in the two opposite directions, increasing news accuracy overall. Conversely, where consumers have homogeneous beliefs, the bias in the consensus is uniformly reflected in the news.

In this context, the direct exposure of locals to migrant settlement at the border may have increased opinion heterogeneity, pushing slant down in aggregate terms. This variability may have also been channeled by the area's recorded presence of humanitarian help from both local and international NGOs (La Cimade, Oxfam, Caritas and Doctors Without Borders, to cite a few). The ideology remained more homogeneous the further away from the actual events, which contributed to the predominance of the anti-immigrant tone. It is profitable to accommodate beliefs since it allows local outlets to gain market from national outlets. This finding is also broadly in line with George and Waldfogel, 2006's argument that local news may adjust their target, given national news penetration. The contact-versus-mere-exposure paradigm put forth in Steinmayr, 2021 is another related perspective. Directly seeing the emergency may have led some of the local news consumers to empathize with the humanitarian difficulties, in the communities closest to the border. As remote municipalities lacked the direct contact element, a general negative reaction appeared to prevail. Accordingly, a graph of hate crime incidents that was measured à la Romarri, 2020 demonstrates that hate crime trends increased more substantially in the farther province. Moreover, this framing shift is documented to matter for voting patterns at coalition level for the general elections. According to studies such as Benesch et al., 2019; Djourelova, 2020 and Keita et al., 2021, news powerfully influences readers' sentiments. This contribution departs from these works by letting supply shocks in media discourse be endogenous, and causally derived from shocks in migration presence. This result also relates to a rich and surging literature in migration economics that investigates how migrants' arrivals impact attitudes toward them (see Table B.1 for a set of these papers). The media component, key in this study, is touched on superficially in these references. Finally, while utilizing a novel context and original data, this work connects to a body of studies in political economics that use text-analysis techniques to analyze the dynamics of politically charged news content. A thorough review can be found in Gentzkow, Kelly et al., 2019.

The rest of the paper proceeds as follows: the next section reviews the literature related to this contribution. Section 2.3 explores the setting and context of the study.

Section 2.4 details the data and measurement, while the core analysis follows in section 2.5. Section 2.6 addresses the potential mechanisms and implications of the main results, continuing with a set of robustness tests. Finally, the last section provides concluding remarks.

2.2 Literature

This study adds to the empirical literature in migration economics that examines asylum migration. It also connects to a number of political science and political economics contributions that examine the eveolution of the news market as well as the impact of media exposure and media content on forming preferences and attitudes.

Related studies in media economics examine the determinants of news market outcomes. These contributions take into account the demand and supply of information in terms of quantity (coverage) and the type of discourse provided (slant). An extensive review of the theory is available in Gentzkow et al., 2015. Anderson and McLaren, 2012 stress the role of mergers in news competition, while Gentzkow and Shapiro, 2010 emphasize newspapers' incentives to tailor slant in the direction of the consumers' ideology. Focusing on local news, George and Waldfogel, 2006, observe that national news penetration influences local news production. Focusing on the language of politics, Gentzkow, Shapiro and Taddy, 2019 propose a text-based measure of language partisanship in the US Congress that takes into account issues with finite-sample bias. The authors note partisan differences in speech have been increasing over time in the American landscape, with a structural positive change sparked by the Republican takeover of Congress in the 1990s.

According to communications literature, media coverage and slant are two key factors that influence how people perceive a subject (Scheufele & Tewksbury, 2007). The terms *agenda-setting* and *framing* were employed in the taxonomy for this body of literature to describe, respectively, i) the relation between the news coverage of an issue and its perceived importance by the mass audience and ii) the implications of different portrayals of a topic on audience perceptions. News markets not only reflect but also shape personal preferences. Prat and Strömberg, 2013 overview the research on the connection between the provision of information and political attitudes. Numerous studies uncover evidence of the media's persuasive effects on policymaking and political preferences by means of radio (DellaVigna et al., 2014; Strömberg, 2004), print (Gentzkow, 2009; Snyder Jr & Strömberg, 2010), TV Campante et al., 2018; Facchini et al., 2017; Gentzkow, 2006 and the internet (Falck et al., 2014).[50] Importantly, media can also impact migration-related outcomes. de Coulon et al., 2016 observe that higher coverage of migration and crime increases

[50] See also the work of Iannelli et al., 2021 who consider several media channels and describe the dynamics in the distribution of sentiments towards immigration in Italy around the 2018 election campaign.

the return migration intentions of the involved minorities, as found for the case of Romanian immigrants in Italy, given state TV coverage of a crime committed by a Romanian immigrant in 2007. Exploring events involving the same migrant crisis as this paper, one of the conclusions of Battiston, 2020 is the effective relationship between shocks on public attention and rescue efforts in the Mediterranean. Djourelova, 2020 reveals that the Associated Press (AP) policy of forbidding the use of the term “illegal immigrant" resulted in milder views toward immigration among the AP’s frequent readership. Keita et al., 2021 collect crime-related news content for Germany and take advantage of a local news outlet policy change, to find that consistently displaying criminals’ origins, especially when offenders are natives, makes natives less opposed to immigration. In contrast to the work of these scholars, here the question is posed in reverse: news outlets are allowed to change their production endogenously and emphasis is placed on how migration-related events impact the news market.

Finally, this study relates to a growing body of research on how immigrants’ presence or proximity affects on the local attitudes and preferences. In Alesina and Tabellini, 2020, the views of destination countries on immigration can be framed along two basic dimensions: an economic and a non-economic, cultural one. The authors note that while immigration inflows are often found to provoke a stronger right-wing backlash and conservative ideology, some contributions instead observe a positive reception or more nuanced effects, found prevalently in cases where natives are exposed to newcomers with a repeated interaction. For this research, the 2010s were of specific interest, with the EU refugee crisis becoming a priority on the political agenda of EU countries. Table B.1 reviews the findings of some of the key contributions in this expanding literature, examining the links between immigration shocks and the political outcomes they influence.

Among these studies, Steinmayr, 2021 focuses on Upper Austria and uses the Austria-Germany border to discriminate between municipalities that hosted asylum seekers and had frequent interaction with them and municipalities that only experienced their transit. The author posits that repeated interaction with the new minorities will promote native acceptance, which is broadly in accordance with the contact theory of social psychology (Allport, 1954; Pettigrew, 1998). Conversely, exposure without contact discourages exchange and breeds hostile sentiments. The empirical findings show that there is this ambivalence in the case of Upper Austria. Campo et al., 2021 explore the effects of the Italian refugee crisis on voting for anti-immigrant parties within the Italian context. Focusing on the national dispersal policy, strongly reinforced in 2014 by the Italian Ministry of Internal Affairs, the authors find that anti-migrant voting, as measured by the difference between 2018 and 2013 election outcomes, concentrates in municipalities that hosted migrant centers. Similarly, Bratti et al., 2020 observe that proximity to municipalities receiving asylum seekers increased support for populist parties in the referendum results, thus reducing left-wing support.

This paper departs from these contributions in several aspects. First, the geographic dimension differs. The interest here zooms into the region near the French border, thus drawing attention to events taking place at an internal EU border. Cross-country borders within the EU area were important settings in the light of the migratory crisis,[51] they have been receiving less institutional attention than the exterior EU borders.[52] The current article also emphasizes as a critical outcome a better understanding of the media market, which is considered more superficially in the literature. Importantly, the focus on a localized setting results in an identification strategy that enables in-depth investigation of this crucial yet underexplored information channel.

2.3 Context

2.3.1 Italy's Migrant Crisis and the Controls at the French Border

During the 2010s, several undocumented migrants landed in Italy with the intention of rejoining family members and contacts in other European countries.[53] In 2014, an allocation policy was implemented by the government to strengthen the pre-existing, insufficient reception system. However, several migrants attempted to continue the journey instead of having their status regularized (Capitani, 2018; Colombeau, 2020).[54] A typical gateway employed by migrants was located on the coastal border between France and Italy, in the north-western region of Liguria.[55] The The geography of Liguria, a short strip of land, extends east and west (Figure 2.3.1 displays its localization). On its northern boundaries are the Maritime Alps and Ligurian Appennines, while Mediterranean Sea is on the South. Mountains delineate the French border region as well, making the coastal border town of Ventimiglia a crucial point of contact with France.

Following peaks in arrivals in southern Italy, the French local authorities introduced a militaristic border control in June 2015. This was done to push unauthorized migrants who attempted to reach France through the coastal gateway back to Italy, specifically to the border town of Ventimiglia. In the immediate wake of the policy's implementation, the local charity Caritas Intemelia recorded two hundred migrants seeking refuge on the streets; nonetheless, these numbers continued to rise during the summer months. Due to the occurrence of terrorist attacks, in late 2015 France

[51] see Cimade, 2018.

[52] Frontex only collects data on illegal border crossings at the external EU frontiers. https://frontex.europa.eu/we-know/migratory-map/

[53] The international Organization for Migration (IOM) reports 62692 undocumented migrants entering Italy by sea in 2011, compared with 4406 and 9573 respectively in 2010 and 2009.

[54] Once landed in Southern Italy, migrants could submit an asylum application. As importantly mentioned in Campo et al., 2021, this procedure is remarkably lengthy.

[55] Others were Bardonecchia, Como, Brennero (Capitani, 2018).

declared a state of emergency, thus officializing the border closure. After a second peak in May 2016, several NGOs came in support of the emergency, and the Italian provincial authority opened a temporary Red Cross reception center. In May 2016, the Italian central government established a bus system to transport some of the migrants from the Ventimiglia region back to the major migration hubs in southern Italy. Nevertheless, Ventimiglia's border only saw a significant decline in arrivals in late 2017 as a result of a set of policies at the EU and national level which effectively decreased the number of migrants attempting the Central Mediterranean Route. In particular, Italy had signed a Memorandum of Understanding with Libya in February 2017 (which was later extended and is still in effect as of 2022) with the intention of cooperating with Libyan coast guard authorities to prevent the boat lifts. Sourced by NGO La Cimade, Figure A.1 is a good summary of the time line and geography of the main events.

Structured data are lacking on the presence of migrants in Ventimiglia. However, in 2017 NGO Caritas Intemelia collected a count of meals distributed to migrants. Figure A.2 in the Appendix reports a peak of 12500 migrants transiting in the area in July 2017. For comparison, Ventimiglia's population is approximately twenty-four thousand residents (Italian National Institute of Statistics [ISTAT] 2019). Despite measures being taken, the situation persisted over time. With some seasonality, migrant arrivals in Ventimiglia were also observed in 2018 and 2019.

2.3.2 Liguria and the Provinces of Interest

Given that the events of interest occurred at the western border, commuting distance from the border proxies the likelihood that locals will be subject to the migrants' settlement. The provinces are chosen for this study because of the morphology of the area of interest as well as from the intention to maintain an internally valid specification. This limited location enables greater control against confounding occurrences of other events linked to the migration crisis in Italy. Thus, the provinces of Imperia and Savona-the border and its neighbor respectively-are selected for analysis. The question of whether the results apply to more general circumstances arises from such a localized selection.

To better understand how generalizable this study is, Figures A.3 and A.4 depict the distributions of several socio-demographic variables for Italian provinces, estimated by kernel densities. The red and blue dashed vertical lines on the graphs indicate where Imperia and Savona, respectively, lie on the distribution. As shown in Figure A.3, Imperia has a relatively higher percentage of cross-border commuters. This aspect importantly highlights that greater border exposure is found in the areas of higher treatment levels. Regarding the other variables, the two provinces tend to appear comparable to the rest of Italy. This holds in terms of total shares of commuters, employment rates, skills distributions of the employed population, shares of immigrant population. Regarding the main immigrant origins, the areas of study present higher shares of population from the American continent.

Figure A.4 depicts vote patterns from 2008 and 2013 for the Chamber of Deputies. With respect to the rest of Italy, the two provinces have comparable values of turnout and appear to lean more to the right, with Imperia experiencing higher right-wing incumbency than Savona.[56] Besides these trends, a right-wing shift did appear in the area of study in the post-migration crisis elections of 2018. The right-wing coalition obtained on average 28.97% of votes for the Chamber of Deputies in 2013, and this increased to 44.94% in 2018. Left-wing coalition votes decreased from 23.89% in 2013 to 18.08%. To better understand the role of some of these patterns, results section 2.6.3 allows for possible heterogeneous outcomes by initial political preferences, as well as by other socio-demographic characteristics.

Figure 2.3.1: Area of interest, Liguria

Notes: A reference map of the region of interest. A close-up view of the region of Liguria is on the left. In the west is the border town of Ventimiglia. The other labels designate the capitals of each province in the region: Imperia, Savona, Genova, the region's capital, and La Spezia. Imperia's province is in blue, while Savona's province is in green. Grey-colored provinces are not in sample. The map of Italy on the right shows Liguria highlighted in blue.

2.3.3 Treatment and Identification

The border shutdown in June 2015 deterred migrants from crossing over to France. In a number of reports, the location was dubbed as “Italian Calais" because of the similar bottleneck situation and precarious living conditions that were endured by migrants trying to enter the UK from France. The area's topography made it difficult for displaced people to locate easy alternative ways to cross the border. Although some immigrants thought of taking a different route to the north across the mountains, this option was unpopular because it was arduous and perilous (Welander, 2017).

[56] For both provinces, 2013 constituted a relatively high success for the newly born anti-system, web-spread populist movement Movimento 5 Stelle (M5S).

It is important to note that both before and after the border policy, migrants were transiting the entire sample region. Once the border closed, however, the border area was suddenly exposed to groups of displaced people in precarious conditions, sheltering in and around the town. At the same time, natives in the area were in more or less direct contact with the border, depending on their geographic proximity. For instance, the top-left graph of Figure A.3 shows that more cross-border workers reside in the border province (Imperia, in red), compared to the province further away (Savona, in blue). Therefore, the identification strategy adopted here is based on the likelihood of natives to be exposed directly to the border events fading away the more distant their municipality is from the border town. The preferred distance measure is commuting time, because it better captures actual proximity given geographical differences.

Data on commuting distances are sourced by ISTAT, which calculates drive times from the centroids of each municipality, considering different road types and assuming an ideal condition of zero traffic. The degree of proximity interacted with the post-June 2015 time interval will determine the treated areas. The causal identification of this approach lies in the comparability of the municipalities across distance, and in the assumption that absent the border events, the municipalities in this study would have followed equal trends. To ensure this is the case, the empirical approach will explore the balance of the sample, allow for the presence of several covariates, and perform robustness checks with respect to the presence of different province-level time trends, or different forms of proximity to capture the degree of treatment. More details follow in the sections below.

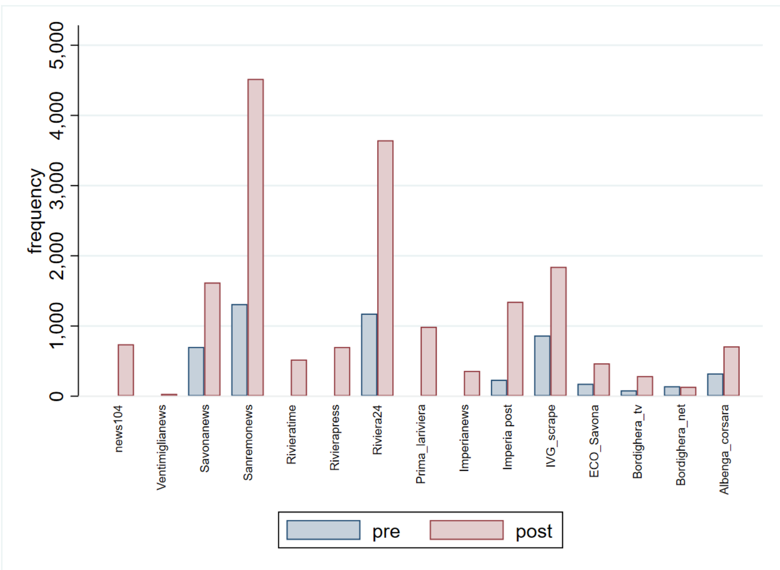
2.4 Data and Measurement

The dataset was created by gathering a corpus of 57,589 migration-related internet articles from 2011 to 2019. This corpus represents most local online outlets present in the two provinces of interest for the time span considered. Then, with a month-year frequency, data at the article level are aggregated to a panel of municipalities. The procedure for gathering data and the text-based metrics are given in the paragraphs that follow. Further information is supplied in the Appendix sections 2.D, 2.E and 2.E, for the sake of concision.

2.4.1 News Data

The news sample was collected with a web-crawling algorithm that individually scraped each relevant news outlet's website. Articles were gathered for each local outlet under consideration if any of the stemmed variants of the following keywords appeared in the text: "migrant," "immigrant," "foreigner," "non-EU citizen" (It., "extracomunitario"), or "displaced person" (It., "profugo"). Additionally, a second web-crawling algorithm extrapolated each website's news count over time. Despite not formally capping the time period for data collection, 2011 to 2019 was chosen as the time period for the data due to restrictions on data availability. When choosing outlets, all local news sources that could be located somewhere within the region and time period of interest were selected. Importantly, this includes outlets that appeared after the policy went into effect. This choice was motivated by the goal to produce statistics representative at the municipality level. Following data collection, a geocoding process was used to map article-level data to municipalities. Working with this statistical unit enables the data to be matched with information on geography, politics, economics, and demographics. [57] Since one text-based measure requires lagged or led information for its development, the final panel covers the period between January 2012 and December 2018 (details follow in this section). Simple Google searches of the kind, “Ventimiglia [or other Municipality in the area] news" were paired with Google Trends searches, restricted geographically in the Liguria region,[58] to extrapolate the universe of the local online newspapers in the provinces. Google Trends Conveniently shows correlated term searches. For example, searching in Google Trends for the online outlet *Sanremonews*, would return correlated searches from users in the region for *Riviera24* and *Prima La Riviera*, which are outlets of interest as well. Figure 2.4.1 displays the universe of the employed news outlets, distinguishing counts by before versus after June 2015. In sum, 57,589 articles were collected, of which 43,085 are from 2012, coming from a total of fifteen news sources.

Figure 2.4.1: Sample collection, text corpus by news source



Notes: Distribution plot of the news in the sample, by news outlet. Blue bars represent data for the pre-treatment period while bars in red represent post-treatment frequencies.

As mentioned above, each source’s collected articles included terms connected

[57] Data inaccessibility excluded sources that had been discontinued at the time of data collection. To the author’s knowledge, however, their number is insignificant.

[58] The most granular geo-localization possible in Google Trends, for the area of interest.

to migration. The process specifically extracted each article's title, subtitle, and full text content, as well as certain metadata, including the author's name (when provided), the article's date, and a tag (if available). It's important to note that not every local outlet considered serves the same areas equally. Although online news is, in principle, accessible without any geographic boundary, local outlets tend to serve a particular area by tailoring their content and advertising revenues to the readers within their coverage. This implies that the geographic distribution of each local outlet may vary, and it is crucial to know this information to determine which news is pertinent in each location.

Direct information on which local online outlets serve which areas is unobserved. However, a reasonably close proxy can be obtained by tracking Google searches for the names of the outlets over time and by municipality. These data are retrieved via Google Trends. The software returns i) a rating for each town based on the volume of searches for any term, such as "Sanremonews,", during a certain time interval. The scale for this rating, which ranges from 1 to 100, is normalized by all Google searches combined. The platform also provides ii) a rating over time based on search traffic for any term with the option to compare it to up to four other terms. This rating spans from 1 to 100 and is normalized across sources by taking a common comparison term.

With this knowledge, the measurement of news coverage of migration simply involves the log count of the number of articles that for each municipality returned a match within the given month-year. The exploration of agenda-setting will use this as the baseline outcome measure. Each text-based measure Y_{mt} for municipality *m* at time *t* is resulting from a weighted sum of y_{imt} values for articles i associated with municipality *m* from Google Trends, as in equation 2.1.

$$Y_{mt} = \sum_{i \in N} w_{it} y_{imt} \tag{2.1}$$

Three different geo-localization techniques are applied to assign the distribution of weights w_i across municipalities and time:

1. *Google searches for each outlet, by municipality, varying in the before versus after time range* are employed to match articles with the municipalities they serve. The construction of weights for each article to each municipality is detailed in Appendix section 2.D. Importantly, measures derived with this matching reflect how demand (search traffic) evolves over time for these news items, both pre and post-border-closure events of June 2015. The baseline estimations adopt this measure.
2. *Google searches for each outlet, by municipality, before June 2015* are employed to match articles with the municipalities they serve. The construction of weights for each article to each municipality is detailed in the Appendix section 2.D. Importantly, measures derived with this matching reflect the demand

(search traffic) for these articles *only* before border closure. This procedure is used in the extended analysis to check whether results are driven by a change in the distribution of demand for these outlets.

3. *No Google Trends data.* To shut down the demand component present in the procedures above, this alternative geocoding procedure assigns news articles to municipalities based on the location of the outlets' headquarters. Each outlet is allowed to cover municipalities within a distance of twenty kilometers (an alternative fitfteen and twenty-five-kilometer range were also tested for robustness). The local news source's articles will all carry the same weight in all locations within this radius. This procedure is used in the extended analysis to check whether results are affected by articles-municipalities in which (pre-existing) demand is strongest.

Google Trends censors locations below a certain level of search traffic. To circumvent this issue, an imputation process that uses a first neighbor technique and information about commuting times (Italian Census 2011, ISTAT) extends the data.[59] Details are presented in Appendix section 2.D. Additionally, Google Trends searches for the two most popular sources—*Sanremonews* and *IVG*—are contrasted with searches for a set of alternative, reasonably popular internet search terms—"accident" (It., "incidente"), "pizzeria," "recipe" (It., "ricetta")—for the region of Liguria. This is done to make sure that the readership size for the local outlets collected is of economic relevance. The search comparisons are plotted over time in Figure A.5. The graph shows that local news is very much comparable to this set of search items, which suggests that the local readership is substantial. Figure A.6 complements this information by plotting trends on internet usage in Liguria, compared with the rest of Italy, and based on ISTAT statistics.

Some of the main indices of interest rely on the content of news, assessed with text-analysis techniques. The next section provides a detailed description.

2.4.2 Text-Based Measures

The document text for each article in the corpus is made up of the article's title, any headers or subtitles, and the text itself. The content is cleaned with pre-processing practices which are common in text-analysis applications.[60]

[59] A robustness test confirms the main findings without this imputation step.

[60] Text is pre-processed with the removal of punctuation, numbers, and *stop words*-words that are frequent in texts and serve as building blocks for sentences, but do not add to the sentence content (e.g. *and, in, of, with, to,*). Then, words are stemmed to remove their endings (Bouchet-Valat, 2020). Upper case (proper) names are removed (except if at the beginning of a sentence), and all words are set to lower case.

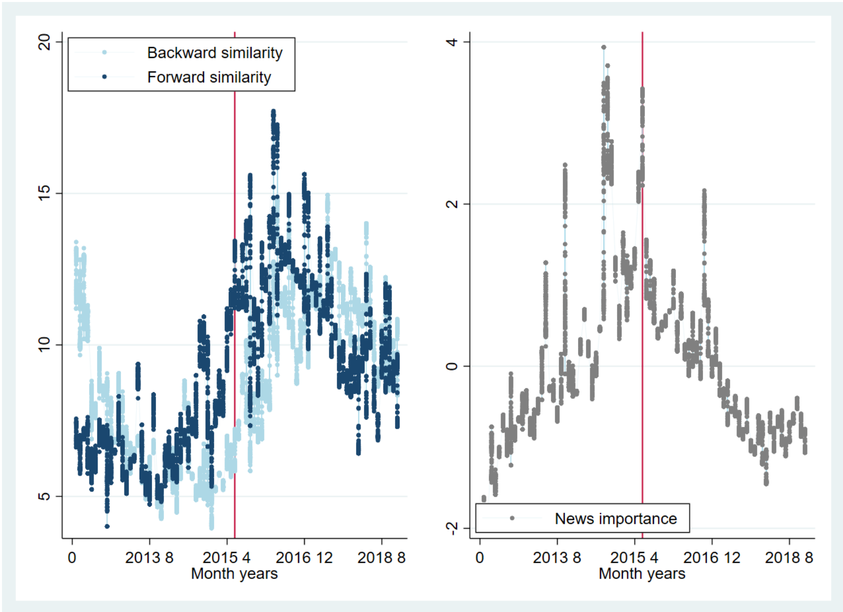
The text-based measures are based on *bag-of-words* approaches.[61] These procedures entail creating a matrix that provides term frequencies by documents; these matrices are known as *document-term matrices*, and they are constituted by documents in their rows i and terms in their columns j.

In line with Gentzkow and Shapiro, 2010, this study uses bi-grams and tri-grams (phrases of two and three words) rather than uni-grams (single words) as the terms of interest to calculate frequency statistics. Using combinations of more than one word usefully captures some word dependencies that would be otherwise discarded. The frequency of n-gram j in document i is specified as tf_{ij}=*term frequency*. For n-gram j, its *Inverse document frequency*= idf_{ij} is defined as the log of 1 over the share of documents containing n-gram j. The product of the term frequency and the inverse document frequency ($tf - idf_{ij}$) will be the metric of interest for cell ij in the document term matrix. The recommended frequency statistic used in text analysis tasks is typically this measure. While mid-frequency words are often regarded as the most salient in this framework, alternative measurers like simple counts or frequencies tend to overvalue extremely rare and extremely common n-grams.

News Importance:
An index of news importance is computed from this information, with an approach borrowed from the patents' literature (Kelly et al., 2021). This metric combines two indices: a *novelty* and an *impactfulness* indicator. While the former is based on the similarity of article i with past articles (higher *backward similarity* indicates lower novelty), the latter relates to similarity of article i with future articles (higher *forward similarity* represents higher impactfulness). This measure is employed to explore how new content appeared geographically with the advent of the French border policy. The assumption made to adopt this measurement, which was validated for patents in Kelly et al., 2021, is that the text-based importance of patents is comparable to the text-based importance of news data. Figure 2.4.2 suggests this is the case: plotting the components of the news-importance variable-as well as the composite index over time, this measure accurately captures the shock of June 2015, appearing as a peak in the news importance time series. A detailed explanation of this procedure is presented in Appendix section 2.E.

[61] These constitute a simple and standard technique to represent a document as a function of its text. In the simplest version of this method, singular words and their frequency are the units of interest. The name *bag-of-words* derives from the fact that information on the words' ordering is discarded. As a straightforward extension, scholars considered replacing single words with pairs and triplets of words. To some extent, this complication allows tracking word combinations that better represent a sentence's meaning. See Gentzkow, Kelly et al., 2019 for a detailed review of these and alternative methodologies.

Figure 2.4.2: News novelty, impactfulness, and importance over time



Notes: Data visualization for backward similarity (the inverse of news novelty) and forward similarity (corresponding to impactfulness) in light and dark blue, respectively, in the graph on the left. In grey on the right side is news importance over time. The red line represents June 2015, the month of the border closure by the French authorities.

Framing:

A measure of media bias toward right-leaning,[62] anti-immigrant speech is used to evaluate the framing dimension in the local news language. This statistic is referred to as *media slant* in what follows.

Articles in the corpus are classified, or labeled, into a dummy variable that takes a value of 1 if the classification procedure predicts the article to be anti-immigrant oriented, and 0 otherwise. This prediction is based on a supervised machine learning approach. This method uses text that has already been classified and labeled as 1 or 0 to create the *training sample*. The training sample's text frequencies are then used to create a predictive model for the dataset's local news items (i.e., the unlabeled data). The data derive from a balanced collection of regional and national news articles that either clearly express or do not clearly demonstrate an anti-immigrant orientation. This information derives from both survey and anecdotal evidence, and details are given in Appendix section 2.E. News items classified as 1 in the training sample belong to newspapers *La Verità* and *Il Giornale*, while text labeled 0 is extracted from *L'Unità News* and *Il Secolo XIX*. Articles from these sources are extracted in the same fashion as for the local news corpus.

Two alternative models are used to classify local news in the binary variable: i)

[62] The rationale for focusing on right-wing partisanship comes from the context of interest. As several authors point out (Bratti et al., 2020; Campo et al., 2021), anti-immigration positions in Italy emerged from right-wing, populist parties (*Lega* and *Fratelli d'Italia* primarily, but more generally in the right-wing coalition).

a regularized logistic regression with elastic-net penalization and cross-validated tuning parameters (Friedman et al., 2009); ii) an inverse regression model by Taddy, 2013. The two models are compared by cross-validating the training sample and comparing the predictions of the models with human predictions. The human predictions are obtained with *Amazon Mechanical Turk*. Validation results suggest similar predictive performance for the two alternative models, with a slight preference for the use of Taddy, 2013's measure, which will be adopted in the baseline analysis. Figure 2.4.3 shows the evolution of the baseline slant measure, which tends to grow over time in the whole sample.

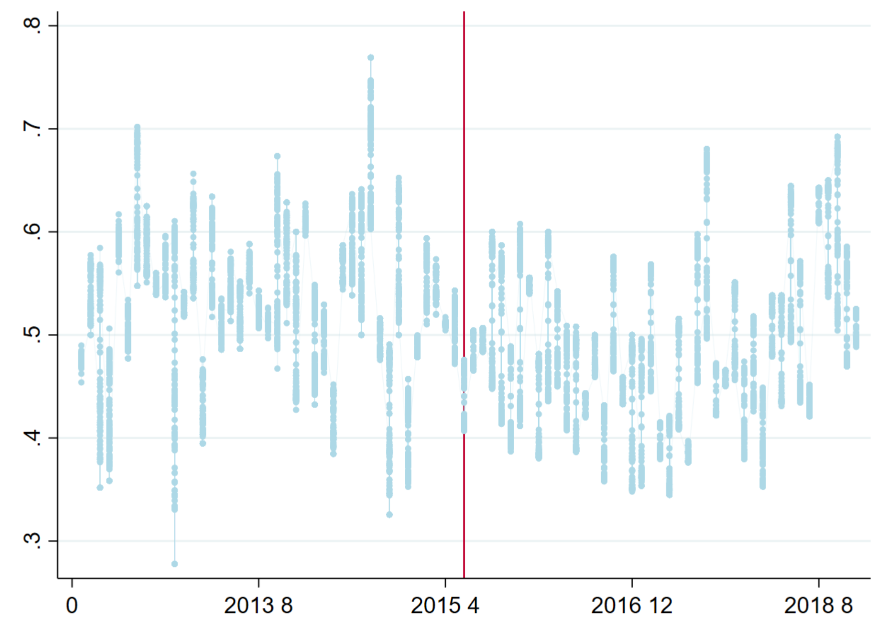
In the Appendix, Figure A.7 predictions resulting from this algorithm are explored. The figure reports frequent terms that return the lowest and highest predictive probabilities of containing anti-immigrant language. The expressions in orange at the top, which least predict anti-immigrant language, are mild expressions to refer to migrants (e.g. "migrating person," "migrating refugee") or terms related to migrants' rights (e.g. "fundamental rights," "protection system"). Terms in the most likely anti-immigrant news (in violet) relate, for example, to legal issues (e.g. "preliminary hearing," "plaintiff"), and expressions of concern on migrant flows (e.g. "uncontrolled immigration"). Table 2.4.1 accompanies the figure with a small list from local headlines in the sample. Appendix section 2.E digs into the construction of this text-based measure in more detail and provides information on the validation procedure for this variable. Finally, as mentioned above in the geo-localization section, the classified articles are combined into a municipality-level metric that can be read as the proportion of migration-related local news that is classified as containing anti-immigrant language.

Table 2.4.1: Anti-immigrant slant: Selected examples of the results

Title	Source	Period	Label
En., They sneak onto "commuter trains" to return to Italy after being expelled: two arrests *It.,* Si intrufolano sui "treni dei pendolari" per rientrare in Italia dopo l'espulsione: due arresti	riviera24.it	Jan 2012	1
En., Giovanni Toti intervenes on the migrants matter: "We should not allow that Italy becomes a big refugee camp for Europe" *It.,* Giovanni Toti interviene sulla questione migranti: "Non si può consentire che l'Italia diventi un grande campo profughi dell'Europa"	sanremonews.it	Jun 2015	1
En., Ventimiglia: police reports two migrants after a theft in Carrefour supermarket *It.,* Ventimiglia: la Polizia denuncia due migranti dopo un furto al supermercato Carrefour	Imperia Post	Nov 2018	1
En., Call from the regional council to promote the diffusion of different cultures *It.,* Bando della Regione Liguria per promuovere la diffusione delle diverse culture	bordighera.net	Jan 2012	0
En., Women, migration, and entrepreneurship, a congress at the Priamar *It.,* Donne, migrazioni e imprenditoria un convegno al Priamar	ivg.it	Mar 2015	0
En., Ventimiglia: another 144 packed meals were delivered today by the Red Cross to migrants *It.,* Ventimiglia: altri 144 pacchetti alimentari consegnati oggi dalla Croce Rossa ad altrettanti migranti	sanremonews.it	May 2016	0

Notes: Examples from the predictions of Taddy, 2013's model on the local news sample.

Figure 2.4.3: Anti-immigrant slant, time series



Notes: Plot showing the evolution of the predicted slant levels over time. The red line indicates the French border closure in June 2015.

2.5 Empirical Strategy

This study employs the baseline model:

$$Y_{mt} = \alpha_m + \delta_t + \beta_1 dist_m * Post_t + \Gamma X_{mt} + \epsilon_{mt} \tag{2.2}$$

where, for municipalities $m \in \{1, ..., 132\}$ and month-year $t \in \{Jan2012, ..., Dec2018\}$, we observe media outcomes Y_{mt}. Month-year and municipality fixed effects are included. β_1 constitutes the coefficient of interest and corresponds to the interaction term between the post-June-2015 dummy, and commuting distance (in minutes) to the border area. In this sense, the degree of treatment corresponds to the likelihood of individuals living in municipality *m* to be directly exposed to the border policy and migrants' settlement. The degree of treatment decays linearly with distance.[63]

X_{mt} is a vector of controls that vary with time and municipality. In terms of news information, these involve the log of total news published in the local outlets, an average word count per outlet, and the count of outlets per municipality. Sourced by ISTAT, demographic variables are population (in logs), population density and the share of population above 65 years of age, immigrant population stocks (in logs), as well as inflows and outflows. Additional covariates are the average taxable income per capita, extracted by tax registers deriving from the Home Office and, varying at province-year level, a crime-rate variable. All specifications also control for the time distance from the administrative and general elections. The dates and years of local elections are not uniform in the sample, thus a variable is created counting the months to the next election for each municipality. General elections are held at the same date in the whole country. The time distance in months to these elections is therefore interacted with distance from the border, to make sure results are not driven by this alternative set of events. Further controls, only available cross-sectionally, are the unemployment rate, the rate of highly educated population, altitude levels, and superficial area, all collected from the 2011 Census (sourced by ISTAT). These are included in the balance analysis as well as in a set of extended results. Table B.2 represents the summary statistics for these variables.

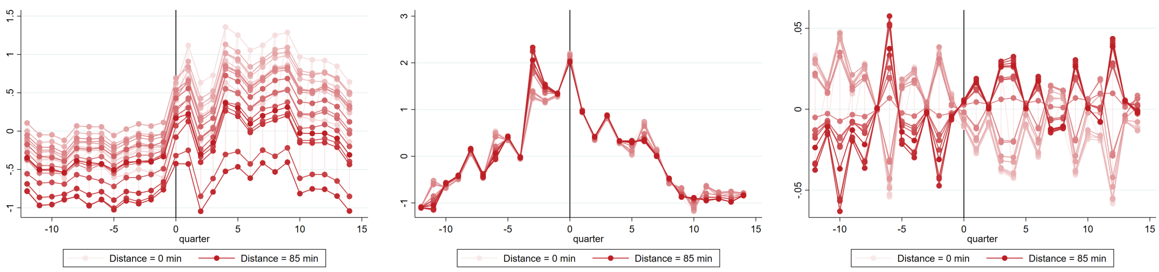
Balance-test statistics are presented in Figure A.8, to test for pre-existing differences in the covariates along commuting distance. The estimates result from an OLS specification on the pre-policy subsample, accounting for time fixed effects. All variables are standardized to ease comparability. The table indicates that some differential across distance existed in the period before the border closure for some explanatory variables. Higher vote shares for the right-wing coalition are found in the 2008 elections closer to the border. In these areas, the overall local news supply was higher and municipalities slightly smaller in area. Generally, distance to the border correlates positively with shares of older individuals, taxable income per

[63] For robustness, a set of extended results allows for different functional forms in the distance-based treatment.

capita, employment and the log of crime events, and negatively to the log of immigrant population stocks. Observable characteristics that vary with time are included as controls in the model, while time-invariant covariates-unemployment, education, altitude and initial political preferences-are further explored in an extended analysis, to investigate any heterogeneous effects depending on their levels.

Below, Figure 2.5.1 plots the evolution of Y_{mt} means over time, by commuting distance (shown in number of quarters of the year before and after the French border closure, which is time 0). From left to right, the plotted outcome is respectively news coverage, news importance, and anti-immigrant slant. Means are computed for each time period and along spans of five minutes of commuting distance. The darker the line, the further the distance from the border: darker red lines indicate means from areas situated at a greater distance, while lighter tones pertain to means from areas closest to the border. The picture shows a clear switch in the link between distance and news coverage at the moment of the border events. A similar switch is observable to some extent for anti-immigrant slant, while importance levels are broadly more uniform.

Figure 2.5.1: Mean outcomes over time, by treatment



(a) News coverage **(b)** News importance **(c)** Anti-immigrant slant

Notes: In this figure, means over time are plotted for the outcome variables Y_{mt}.

2.5.1 Results

News Coverage and News Importance

To what extent did the border closure translate into a mediatic event? To answer this question, Table 2.5.1 presents the estimation results on news coverage on the top-that is, the log count measure of migrant-specific news items-and importance on the bottom-that is, the text-based measure of news similarity with previous versus future content.

In the table, controls are gradually added from left to right. News controls include the number of total news (in logs), as well as an average word count of the articles. These are included in all specifications. All table columns also control for the time distance from the administrative and general elections. Population controls involve the log of population, population density (population per squared kilometer) and the share of population over sixty-five years of age, while migration controls are the log of immigration stocks and the logs of population inflows and outflows. Income per capita and crime are added in column 4. Finally, column 5 allows for the inclusion of a count of local outlets present in the municipality m at month-year t. This covariate is of particular interest for the coverage measure, as it allows exploring how much extent news coverage results are driven with vs across sources.

In all regressions, municipality fixed effects and month-year fixed effects account for the unobserved heterogeneity that is fixed over time, or municipality. At the top of the panel, the interaction coefficients of interest are negative and highly significant, pointing out increased news coverage closer to the border. The size of the coefficient stays stable across the different columns. An increase in commuting distance by 10 minutes corresponds to 5-6% lower coverage of migration in the aftermath of the border events.

Table 2.5.1: Baseline results: News coverage and importance

	Dependent variable: Migrant news coverage (log)				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	-0.005***	-0.005***	-0.005***	-0.006***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.94	0.94	0.94	0.94	0.97
	Dependent variable: migrant news importance				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	-0.002	-0.003	-0.003	-0.003	-0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	11088	11088	11088	11088	11088
Adjusted R^2	0.95	0.95	0.95	0.95	0.97
Municipality FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes
Population controls		Yes	Yes	Yes	Yes
Migration controls			Yes	Yes	Yes
Income and crime				Yes	Yes
Tot. outlets					Yes

Notes: Baseline results for news coverage and news importance: results pertain to a reduced form diff-in-diff model outlined in Equation 2.2. The dependent variable is the log of news counts in the top-panel, and a news content importance index at the bottom. Standard errors are two-way clustered at municipality and month-year level. Controls are gradually added from left to right. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

To dig into the effect's persistency, the left graph of Figure A.9a displays coefficients of an event-study specification, as in equation 2.3, where the effect is allowed to vary by quarter:

$$Y_{mt} = \alpha_m + \delta_t + \sum_{\tau=Q1,2012}^{Q4,2018} \beta_t I[\tau = t] * dist_m + \Gamma X_{mt} + \epsilon_{mt} \qquad (2.3)$$

where m, t and ΓX_{mt} are defined as in equation 2.2 and the set of controls is the same as column 4 (i.e., the richest set, excluding the outlet counts, to avoid controlling for a media-related outcome), and the quarter before the events (Q1 2015) is the reference period. In the figure, a persistent higher coverage the closer to the border is identified. Despite some fluctuation, the size of the effects is relatively stable over time, with values similar to the baseline results. There's some significance in the pre-policy coefficients in this graph. As this could be a concern for the validy of the parallel trends assumption, an alternative event-study specification is presented on the right of subfigure a, where individual seasonal linear trends are added. With this addition, the parallel trends assumption appears maintained and a negative, persistent effect is still present.

News importance outcomes are presented on the bottom panel of Table 2.5.1. Similar to the results for coverage, news importance appears to correlate positively with the proximity to the events. However, the negative coefficient on the interaction term is only significant at the 5% level in the specification of column 5, when controlling for the number of local outlets. Moreover, in terms of size, the effect is less relevant. Given that the dependent variable is standardized, an additional 10 minutes in commuting distance decreases the importance of news by at most 0.03 standard deviations. Figure A.9b presents the event-study specification for this outcome (with a control set equivalent to column 4) and does not show a significant impact. The figure displays no real persistence of these findings and further shows a significantly negative individual coefficient for one of the periods preceding the events. Inference on this outcome is then less robust to parallel trend violations and shall be taken with a grain of salt.

News Slant

Baseline results on anti-immigrant slant are presented in Table 2.5.2. The table structure follows closely the specifications of Table 2.5.1: controls are gradually added from the left to the right and all regressions include municipality and month-year fixed effects. As anticipated, the outcome of interest is the proportion of news items in municipality m that are predicted to be anti-immigrant. Estimation results of Table 2.5.2 indicate that, as a result of the June 2015 events, the slant in local media got relatively higher in less-exposed, further areas. An increase in commuting distance by 10 minutes resulted in a significant rise of around 0.22 standard deviations in the proportion of slanted news. Table B.3 presents some robustness checks.

In the first division of Table B.3, the alternative classification method by Friedman et al., 2010 is employed.[64] In the baseline measure, a label of 1 is assigned to an article, if the predicted probabilities obtained in the predictive model are higher than 0.5. The second and third panels employ alternative threshold probab-

[64] See also Friedman et al., 2009 detailing the R package employed.

Table 2.5.2: Baseline results: Anti-immigrant slant

	Dependent variable: Anti-immigrant slant				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.019***	0.019***	0.019***	0.018***	0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	11088	11088	11088	11088	11088
Adjusted R^2	0.79	0.79	0.79	0.79	0.79
Municipality FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes
Population controls		Yes	Yes	Yes	Yes
Migration controls			Yes	Yes	Yes
Income and crime				Yes	Yes
Tot. outlets					Yes

Notes: Baseline results for news anti-immigrant slant: results pertain to a reduced form diff-in-diff model outlined in Equation 2.2. The dependent variable is an index of right-wing slant for news. Standard errors are two-way clustered at municipality and month-year level. Controls are gradually added from left to right. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

ility scores of 0.55 and 0.45 to assign slant labels to articles. Results from these specifications stay in line with the baseline, both in significance and size.

Proceeding to the table bottom, an alternative specification directly considers the aggregation of probability scores, rather than that of labels, as the outcome variable. Results are presented for both the benchmark index and for the index based on Friedman et al., 2010, leading to similar results.

Finally, an event-study specification is presented in Figure A.9c. All pre-policy coefficients are not significantly different from zero and the post-policy coefficients tend to have positive point estimates. While the coefficients on the right hand side of June 2015 display some fluctuation in their significance, the effect appears quite persistent, and only fading away in the latest months. Further sensitivity analyses for these results are examined in Section 2.6.

2.6 Mechanisms, Implications and Robustness

2.6.1 Mechanisms and Implications

Baseline results suggest the events of June 2015 increased the coverage of migration-related news in the most exposed areas, while the anti-immigrant slant increased relatively more in the municipalities further away. How sizeable are these effects? Focusing on the U.S.-Mexico border in California, Branton and Dunaway, 2009 explore the correlation between Californian news coverage of immigration and distance to the borders, for the period 2004-2005. The authors find that an extra ten miles of distance to the border relates to a 2.6% lower coverage of Latino immigrant news. Comparing with this correlation, in the French-Italian setting a one-mile increase in distance results in roughly 8.7% lower coverage,[65] suggesting a strong salience for the border policy. In the US setting, Gentzkow and Shapiro, 2010 predict an 18 % loss in circulation of an average (national) newspaper if it were to deviate by 1 standard deviation from the profit-maximizing level of slant. Taking this reference as a crude benchmarking, assuming that slant increases maximized profits means that an additional ten minutes commuting distance leads to a gain in news traffic by roughly 3.96%.[66]

To further explore this set of results, this section attempts to distinguish the role of news demand in the slant results. A first analysis relies on alternative geocoding procedures to map the data at article level to a panel of municipalities. As anticipated in the data description, in the benchmark indicators news items are geocoded into municipalities given Google searches for each local news outlet. These searches are allowed to vary over time, implying baseline results contain a component of endogenous variation in the demand for local news over time. Two different approaches are used to address how results depend on this demand-side component. The estimates related to these approaches are presented in Table 2.6.1. In the table, column 1 displays the benchmark estimates for comparison. A first approach involves using only Google searches from before June 2015 to perform the geo-localization step. The resulting estimates for the slant indicator are presented in column 2 of Table 2.6.1. While coefficients shrink slightly, their sign and significance stay robust to this alternative specification, suggesting that the results are not merely driven by an endogenous change in the weights of news traffic over time. A second approach involves shutting down the demand component of these results, by proposing an alternative geocoding procedure: news items are assigned to municipalities according to the location of the headquarters of local outlets. Specifically, each outlet is allowed to cover municipalities within twenty kilometers (while not presented here, an alternative fifteen and twenty-five-kilometers range were also tested and produced similar findings). For all municipalities within this distance, articles from each local news source have the same weight. With this alternative construction, the slant effects presented in column 3 of Table 2.6.1 are sizeably reduced. A smaller coefficient of 0.004 is significant at 10 per-cent level. This suggests that the slant differential appears when articles with higher levels of news consumption are given more weight.

All in all, these outcomes suggest that local-news slant is shaped by (pre-existing) patterns in the consumption of news. They are not exclusively driven by switches in traffic, nor do they derive from a mere supply channel.[67]

[65] In the present study, the maximum commuting distance within the first mile from the border is 14.6 mins.

[66] The effect of a ten minute increase in distance after the policy is 0.22 standard deviations in the preferred specification of the baseline, with all controls added but the endogenous outlet count.

[67] The number of municipalities covered in size is smaller when taking the supply-only approach. Therefore, N been equalized in the table to this smaller sample, for better comparability.

Table 2.6.1: Extended results: Supply versus demand

	Dependent variable: Anti-immigrant slant		
	(1)	(2)	(3)
	Benchmark	Pre-existing demand	Supply
Border distance (min) # Post	0.020***	0.017***	0.004
	(0.005)	(0.004)	(0.005)
Observations	5819	5819	5819
Adjusted R^2	0.80	0.82	0.46
Municipality FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
News controls	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes
Population controls	Yes	Yes	Yes
Migration controls	Yes	Yes	Yes
Income and crime	Yes	Yes	Yes

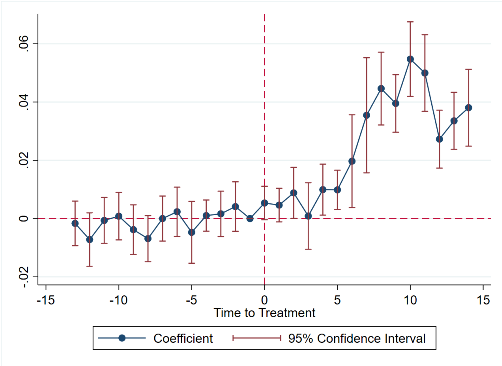
Notes: Extended results on demand versus supply channels. Specifications are comparable to column 4 of Table 2.5.2. Standard errors are two-way clustered. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

George and Waldfogel, 2006 suggest that local news outlets' position in the market depends on the presence of national news. Table 2.6.2 investigates whether slant effects depend on the local versus national news penetration in the local market. These estimates rely on a new proxy variable, constructed with the use of Google Trends, to capture the relative traffic of a particular local source with respect to each of four main national newspapers: *La Repubblica, Il Fatto Quotidiano, La Stampa*, and *Il Giornale*.[68] For each local news in the sample, Google Trends monthly traffic for each local outlet a is obtained in comparison to the traffic for national newspaper b. Then the ratio a/b is computed. Data are then aggregated at the municipality level, as for the other media outcomes. The resulting measure indicates how many internet searches local news received in proportion to searches for national news. In this sense, it serves as a proxy for local news relative penetration vis à vis national outlets.[69] The four measures created represent local news penetration with respect to each of the four main national outlets considered and are plotted over time in Figure A.10.

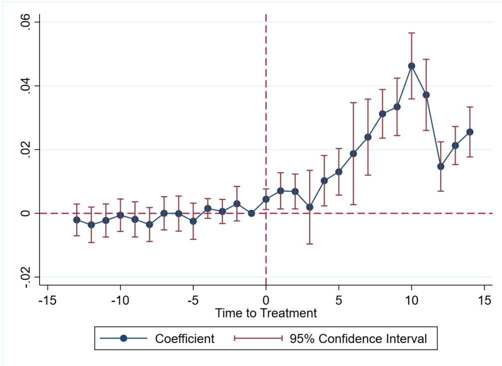
[68] This precise order follows a left-leaning to right-leaning scale, as from YouGov statistics.
[69] See Askitas, 2015 for a review on the scope of Google Trends data for detecting relevant socio-economic trends with high time-frequency, worldwide.

Figure 2.6.1: Migration-related articles, effect on anti-immigrant slant of articles per month.

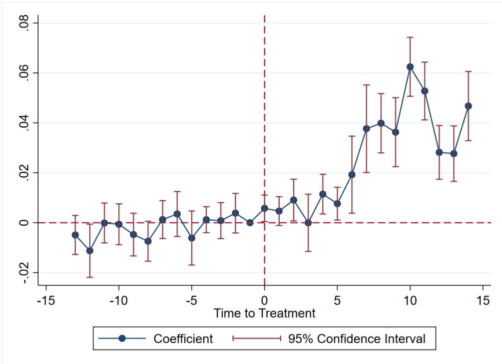
(a) La Repubblica



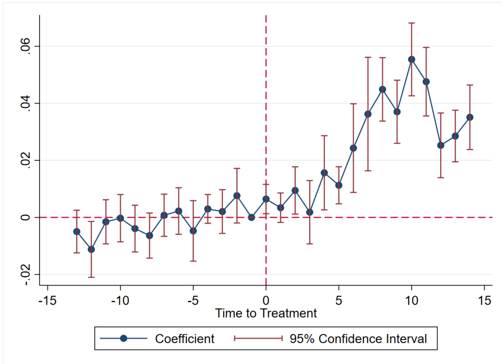
(b) Il Fatto Quotidiano



(c) La Stampa



(d) Il Giornale



Notes: Coefficients plot from an event-study specification. The local-news penetration proxy is the outcome of interest. From the top-left to the bottom-right, the national outlets of reference for the measure are, respectively: La Repubblica, Il Fatto Quotidiano, La Stampa, Il Giornale.

Figure 2.6.1 reports results from an event-study specification as done for the media outcomes. Results suggest that, following the border controls, the relative demand differential for local news was increasingly more positive for the more distant areas. Further, this differential appears to increase over time. This finding suggests that changes in local news penetration and anti-immigrant slant took the same direction.

Building on this, Table 2.6.2 investigates whether and how results on the media-slant index depend on this penetration variable. Columns 1 to 4 add these four relative-penetration measures as control variables separately, while column 5 adds them jointly by considering the score of a principal component analysis (PCA) on the four variables. Columns 6 to 10 report results from a fully saturated model with triple-centered interaction between the distance thresholds, the post dummy, and the level of local news vs national news penetration. In all columns, the policy impact is robustly stable and comparable to the baseline estimates. In the simplest specifications (Columns 1 to 5) local-news penetration does not significantly affect slant. When all interactions are added, however, in columns 6 to 10 we observe some significant correlation between local news penetration and slant that varies with distance and period. Importantly, focusing on column 10, where the PCA score is considered, the effect of the policy turns out to be increasing in the level of local-news penetration. These findings suggest higher local news penetration helps news in the areas further away to increase slant, i.e., local news adapt their readers targeting in response to the market penetration of national news (as proposed in George & Waldfogel, 2006).

Table 2.6.2: Extended results: Relative penetration of local news

	Local vs national news, controls					Local vs national news, interaction				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Local news vs La Repubblica	0.042					0.354				
	(0.100)					(0.385)				
Local news vs La Stampa		0.041					0.402			
		(0.091)					(0.260)			
Local news vs Il Giornale			0.049					0.559*		
			(0.097)					(0.282)		
Local news vs Il Fatto Quotidiano				0.041					0.536	
				(0.132)					(0.639)	
PCA Score					0.023					0.295
					(0.052)					(0.182)
Border distance # Post	0.017***	0.017***	0.017***	0.018***	0.017***	0.019***	0.018***	0.018***	0.021***	0.020***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)
Border distance: Triple difference						0.003	0.003	0.009**	0.007	0.004
						(0.005)	(0.004)	(0.004)	(0.006)	(0.003)
Post # National news						-0.335	-0.320	-0.550*	-0.568	-0.284
						(0.411)	(0.295)	(0.317)	(0.653)	(0.197)
Border distance # National news						-0.003	-0.004	-0.009**	-0.006	-0.004*
						(0.004)	(0.004)	(0.003)	(0.005)	(0.002)
Observations	11088	11088	11088	11088	11088	11088	11088	11088	11088	11088
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Migration controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income and crime	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

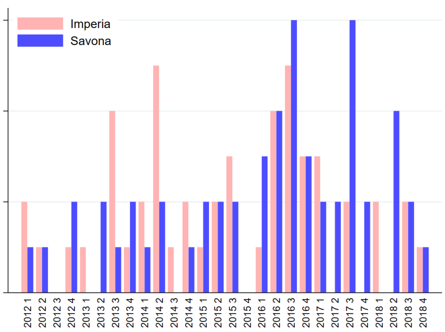
Notes: Extended results, triple differences. Coefficients relate to the dependent variable *anti-immigrant slant*. The set of controls included is equivalent to Column 4 of the benchmark results. Columns 1 to 5 control for the relative penetration of local news, versus each of the four national outlets considered. Column 6 to 10 add all possible interactions between distance, penetration and the post-events dummy, to obtain a fully saturated model. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

One further rationalization of this finding is that local news at the border are more subject to an audience that is also directly exposed to the events.[70] The heterogeneity of readers' beliefs may impact newspaper slant choice, if, as in the model of Mullainathan and Shleifer, 2005, readers seek confirmatory news, that reinforce their beliefs. Local demand for news at the border would then lead, on average, to increase aggregate levels of accuracy. Away from the policy area, ideological readers may gain interest in local news to reinforce their beliefs, thus allowing for local outlets to penetrate the market.

[70] Gentzkow et al., 2018 consider a model of trust in information sources where individuals both receive information from news and from direct exposure to an event, and decide on the information accuracy depending on their own ideology, possibly trusting more news that validate their views.

Finally, results relate to the framework of Steinmayr, 2021, who discusses the opposed implications of contact versus mere exposure of natives to migrants.[71] Figure 2.6.2 is in line with the contact-theory mechanism. It reports a count measure of hate crimes in the two provinces of interest. This figure builds on Romarri, 2020 who investigates the impact of far-right incumbency on hate crimes, employing a database collected by NGO Lunaria.[72] Using the same data, Figure 2.6.2 depicts the time variation of hate crimes, aggregated by province. An emerging pattern reflects a growing incidence of hate crimes after border closure for the further province of Savona.[73] In what follows, these overall results are compared with voting patterns, investigating the implications for political preferences.

Figure 2.6.2: Hate-crimes over time, by province



Notes: Time series of hate crimes, compiled by database Lunaria, used in Romarri, 2020.

2.6.2 Voting Patterns

How do the outcomes found for local news match with aspects of the local political economy? To answer this question, this section explores shifts in voting patterns between the periods before and after the border-control policy.[74] Outcomes presented here derive from a first-differences estimation comparing the 2013 with the 2018 general elections' outcomes in the municipalities of interest.

The equation line is the following:

$$\Delta Y_{mc} = \beta_1 dist_m + \Gamma \Delta X_{mc} + \epsilon_{mc} \tag{2.4}$$

For municipalities $m \in \{1, ..., M\}$, we observe election outcomes ΔY_{mc}, corresponding to the difference in vote shares for a party or coalition in 2018 with respect to 2013, for each of the parliament chambers c: {Senato, Camera}. The treatment is defined as for the text-based results, with β_1 being the coefficient of interest.

[71] This framework is based on the work on social psychology by Allport, 1954. Such a channel is not mutually exclusive with the previous rationalizations.

[72] www.cronachediordinariorazzismo.org

[73] Note the count variable in the period of interest has low variation. This lack of heterogeneity motivates the choice of not running a regression for this outcome.

[74] See paragraph 2.C in the Appendix, for a description on the Italian political context.

Table 2.6.3's specifications all control for population (in logs), the total number of voters (in logs), population density the share of the population over 65, the log of immigrant stocks, income per capita, population inflows, outflows, and crime events (at province level). Distance is standardized. Results on the shares of two explicitly anti-immigrant parties *Lega* and *Fratelli d'Italia (FDI)* are reported jointly in column 1, and separately in columns 2 and 3. No significant effect is found in this section. Results differ when shares are explored at coalition level, in columns 4 and 5. At a higher distance, the left-wing coalition lost preferences to the advantage of the right-wing coalition (which was also composed of these two parties). The framing of discourse in the local news matches with shifts in coalition voting. An increase of one standard deviation in commuting distance indicates 1.4 percentage points increase of right-wing preferences, and a 1.2 percentage points decrease in left-wing coalition votes. Specifically, there's a relative loss in preferences for the Democratic Party, and a relative success for Berlusconi's former party PDL. M5S also gained relative consensus. The bottom side of the table adds to these results, by allowing changes in the two main media variables to interact with distance, to capture potential mechanisms. Adding these covariates shows that the higher the distance from the border positively relates with right-wing success, but this positive relation becomes negative if slant increases. Slant changes appear to be the mechanism through which distance from the border lower the support for the Democratic Party, leading to a switch towards a more populist M5S.

To summarize, this evidence suggests that the border events provoked some changes in the local political economy, in terms of voting attitudes across the main coalitions, and the resulting news slant seems to disfavor the center-left. These patterns share broadly the same direction as media-framing outcomes.

Table 2.6.3: Baseline results: Elections outcomes

Outcome: vote shares	**Anti-immigration**			**Coalitions**		**Turnout**	**Other vote shares**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Lega, FDI	Lega	FDI	RW coalition	LW coalition	Turnout	PD	M5S	PDL, FI
Border dist	-0.006	-0.003	-0.004**	0.010*	-0.010**	0.006*	-0.009**	0.019***	0.014**
	(0.006)	(0.006)	(0.001)	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)	(0.005)
Observations	264	264	264	264	264	264	264	264	264

Outcome: vote shares	**Anti-immigration**			**Coalitions**		**Turnout**	**Other vote shares**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Lega, FDI	Lega	FDI	RW coalition	LW coalition	Turnout	PD	M5S	PDL, FI
Border dist	0.001	0.004	-0.004*	0.011*	-0.036***	0.004	-0.034***	0.040***	0.009*
	(0.008)	(0.008)	(0.002)	(0.006)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)
Border dist #Diff slant	0.027	0.026	0.001	0.003	-0.096***	-0.008	-0.097***	0.082***	-0.021
	(0.021)	(0.020)	(0.006)	(0.019)	(0.014)	(0.013)	(0.013)	(0.017)	(0.018)
Border dist #Diff coverage	-0.001	-0.002	0.001	-0.006	0.013*	0.001	0.006	-0.002	-0.008
	(0.009)	(0.009)	(0.003)	(0.006)	(0.008)	(0.005)	(0.006)	(0.007)	(0.007)
Observations	264	264	264	264	264	264	264	264	264
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results for voting outcomes. This table displays coefficients from a reduced form diff-in-diff model. On the bottom panel, anti-immigrant slant is added as a regressor. The dependent variable is the party/coalition vote shares. Election outcomes from this table pertain to Camera and Senato general elections of 2013 and 2018. In all columns, municipality fixed effects and year fixed effects are included. Standard errors are clustered at municipality level. Controls included are electorate population (in logs), population density, over 65 population shares, logs of immigration stocks, income per capita, population inflows and outflows, and crime events at province level. Acronyms read as follows: FDI is *Fratelli d'Italia*, RW and LW are respectively "right-wing" and "left-wing". PD, M5S and PDL, FI stand for *Democratic Party, Movimento 5 Stelle*, and *Popolo della Libertà, Forza Italia*, respectively. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

2.6.3 Heterogenous Results by Time Invariant Controls

Baseline results suggest that local shocks in migrants-presence created a rise in news coverage in the most exposed areas and a relatively higher increase in anti-immigrant slant in the least directly exposed municipalities. According to the results in the previous section, the framing dimension goes in the same direction as hate-crime rates and voting preferences. Table B.4 adds an heterogeneity study to these findings, to explore to which extent the effects differ across initial education levels (based on 2011 shares of University graduates, as sourced by census data), initial incumbent ideology (i.e., vote-shares for the left-wing coalition in the general elections of 2008), altitude levels (i.e., maximum altitude reached in the municipality), and initial unemployment rates (Census 2011). Column 1 is included for benchmark and is equivalent to column 4 of the baseline tables. The top of the table shows results on news coverage. Evidence suggests that the closest areas to the border receive more news coverage, especially in areas areas with lower altitude (these can be conceived as more urbanized areas, given the region's morphology). Right-wing-slant results are also heterogeneous along altitude levels. In particular, the positive interaction coefficient is less strong if altitude is higher, possibly indicating that the stronger media effects are in the most urbanized municipalities, which lie on the coast. Regarding the other interactions, these are not significant. Results are relatively homogeneous across the socio-demographic characteristics considered.

2.6.4 Robustness to Functional Forms for Distance and Parallel Trends Assumptions

Table B.5 shows robustness tests with respect to alternative functional forms for commuting distance. On the top side of the table, commuting distance enters log linearly, via the transformation $log(x+1)$, where adding one prevents the omission of Ventimiglia from the analysis. At the bottom, a quadratic term is introduced. The table broadly confirms the results obtained via the linear specification, both in terms of direction and significance. A 10% increase in commuting distance implies a decrease in news coverage by 1.6% and an increase in slant by 0.056 standard deviations. The estimated decrease in news importance is not significant in this specification. The results on the quadratic effects do not point at significant non-linearities, leading to the linear specification for distance as the preferred form.

Finally, in Figure A.11, the linear distance specification is replaced by a set of binary treatment diff-in-diff regressions, in which a binary treatment equals 1 if commuting distance is higher than distance n, in the x-axis. The y-axis plots the values of the diff-in-diff coefficient, with p-values and confidence intervals obtained with wild-cluster bootstraps. This approach is motivated by Callaway et al., 2021's considerations, for which average marginal effects from difference-in-difference estimations with continuous treatment estimated by two-way fixed effects may require stronger assumptions to hold, as well as producing weighted averages of the effects, with (positive) weights being sensitive to a set of conditions. The overall take away of the graph is that, despite some size fluctuations, results are robust in sign and significance to the linear distance coefficients.[75] Another robustness analysis involves testing the results to the inclusion of linear time trends that vary geographically. Table B.6 presents estimation results when linear time trends by municipality are accounted for. From the top to the bottom, the coefficients presented relate to coverage, importance and slant respectively. Overall, the results are quite comparable to the baseline estimations, with some negligible variation in size for the coefficients in the coverage estimates; while coefficients for the slant measure effects increase more substantially. The unobserved heterogeneity captured in the individual linear time trends signals a possible underestimation of the slant effect in the baseline specifications. The stronger effect found here may suggest, for instance, the presence of a measurement error that attenuates the baseline results. Overall, however, the main findings stay robust in size and significance.

[75] David et al., 2018 suggest that different approaches in addressing the scale of analysis may induce conflicting results on the drivers of individual attitudes and political preferences. These sensitivity checks around the measurement of exposure would at least partially address these concerns.

2.6.5 Other Robustness Tests

A second battery of robustness tests is performed to allow the possible exclusion of a municipality (i.e., a panel unit). Because the set of municipalities under study is restricted to a small sample, a test is conducted to make sure that the results on the three outcomes are not driven by the presence of a single municipality. Figures A.12, and A.13 reproduce both betas and associated t-statistics for all possible permutations of such exclusions. The figures indicate that both sign and significance of the effects are maintained in all these alternatives. On a similar ground, Figure A.14 summarizes results when a month is excluded from the estimation. Results persist in sign and significance to each of these possible alternatives. A related concern involves the use of an imputation method to extend the original geographic distribution of news, retrieved by Google Trends. Note without imputing the sample substantially shrinks to 38 municipalities. Table B.7 shows that even when restricting the sample to the original non-imputed data, the direction of the results is maintained. Concerning size and significance, coverage results maintain the same sign, although the size of the effect is now diminished. The significance disappears, given higher standard errors. In this regard, note that the standard errors of every estimation are two-way clustered at both panel unit and at time unit, meaning the results are quite conservative. Reassuringly, slant coefficients are very much in line with the baseline estimates.

Another robustness exercise is displayed in Figure A.15. The figure presents possible alternatives to the article count measurement. In the baseline version, all articles are accounted for to explore a measure at the municipality level of news coverage, irrespective of Google Trends weights. This means that too much importance may be given to outlets that count very little for the search traffic in a municipality. To make sure that the agenda-setting results are robust to the presence or absence of very low traffic outlets, regressions in the figure exclude those articles that returned a search-traffic rating lower than n $\in \{5, 10, 15\}$ in Google Trends. To complement this alternative, the figure also shows regressions that exclude articles with very high search-traffic ratings (n $\in \{85, 90, 95, 100\}$). The graph presents coefficients and 90% confidence intervals, from the same diff-in-diff specification (column 4) in the baseline. Reassuringly, the graph suggests that the baseline findings are valid also under this alternative measurement.

Finally, a placebo test confirms that the predictive slant algorithm for articles is not producing a spurious result. A placebo training sample is built such that it is equal to the original training sample, but the predetermined 0 or 1 labels are now randomly shuffled. Then, slant predictions are made on the local news dataset as done for the original measure.[76] Table B.8 shows insignificant coefficients for the placebo-slant measure. This confirms that it is the original training sample, rather

[76] This procedure leads to a vast number of prediction probabilities to be exactly 1/2: these entries are randomly assigned a 0 or a 1.

than a random label assignment, that leads to significant results in the baseline.

2.7 Conclusion

This paper examined how local news markets can be shaped by salient events in the context of the recent European migration crisis and documents a relationship between news-market outcomes and trends in the local political economy. It provides new evidence that local shocks in migrant presence impact the local news discourse, both in news quantity (*agenda-setting*) and discourse (*framing*), though in opposite directions. The identification of these effects follows from a localized geographic and historical setting. A local shock in migrant presence at the French-Italian border in June 2015 emerged from the establishment of a militarized push-back system by the French authorities. The coastal border had previously constituted an important gateway for precarious migrants, intending to leave Italy for other European destinations.

Understanding how news speech evolves is key to understanding potential aspects of the evolution of the attitudes of citizens (Djourelova, 2020; Keita et al., 2021) and language analysis can retrieve rich information on the political landscape that may even go beyond the observed electorate behavior (Gentzkow, Shapiro & Taddy, 2019).

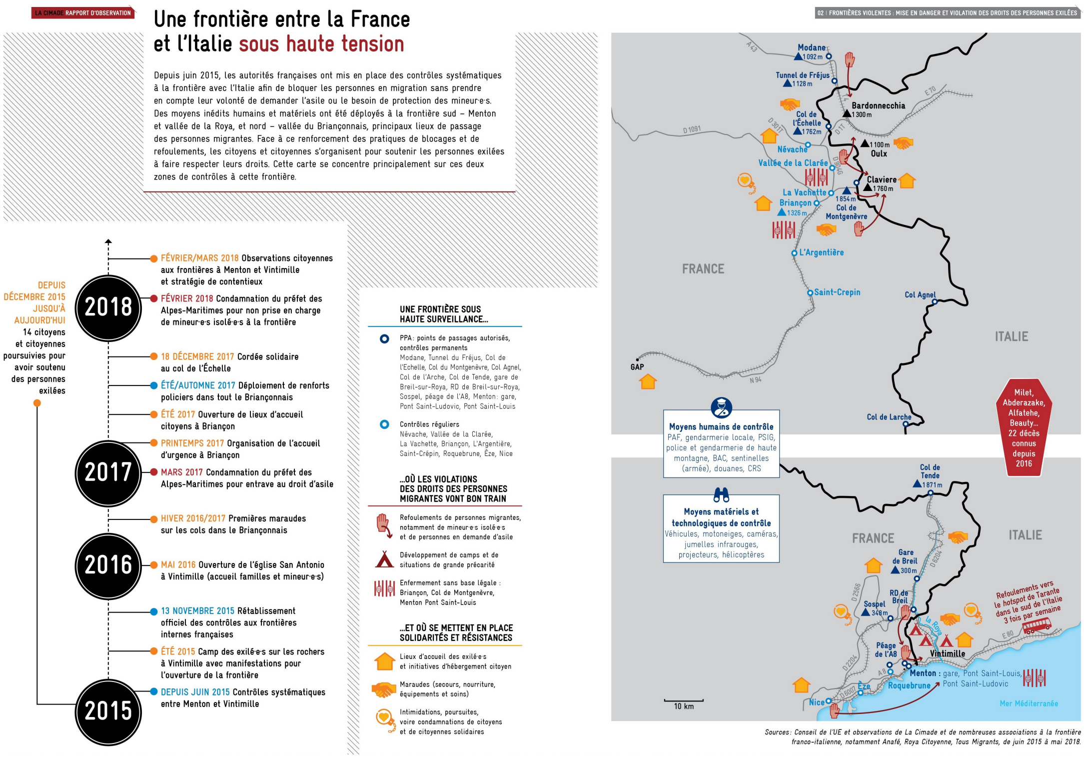
A rich data collection of articles allowed an investigation of two important factors of news production: *agenda-setting*, explored via indices of migration news coverage and news importance; and *framing*, analyzed via a measure of media bias, or slant, towards anti-immigrant discourse. Evidence suggests these border closure events translated into a mediatic shock: the municipalities closer to the event received more migrant-related news. Decreasing commuting distance by ten minutes resulted into 5-6% lower coverage. Also content-importance of these news-*novelty and impactfulness*- was higher the closer to the border, though to a lower and less-robust extent. The share of anti-immigrant news, however, was observed to get relatively higher in the municipalities further away from the border. The study proposes some rationalizations of this finding. Results are found to be driven by articles that can rely on higher (pre-existing) news consumption. Readers' demand for slant in local news may have differed depending on their exposure to the real events. Local vis-à-vis national news search traffic is taken as a relative measure of penetration in the analysis. The relative interest in local news turns out to change in the same direction as slant, after the border policy. Additionally, in the least exposed areas, slant is the strongest where local news gain more market. If local news readers close to the border become more heterogeneous in terms of migration views, local demand for anti-immigrant voicing may be counterbalanced, at the border, by the presence of favourable counterparts. This mechanism can also relate to Steinmayr, 2021's contact versus exposure paradigm. Lower slant levels in the areas closest to the border may reflect the presence of some empathetic attitudes where more contact occurred with the migrants' precarious situation, whilst municipalities further away, lacking this contact component, responded on average more negatively. This line of thought is matched by: i) overall trends in hate crime events, measured à la Romarri, 2020 and ii) vote shares differentials for the general elections, where the left-wing coalition lost support. The baseline results prove robust to several sensitivity checks on the specification of the model and the measurement of the main variables. While focusing on a local setting, the policy relevance of this contribution is broader. This study relates to the importance of international coordination in migration policies (Cimade, 2018; Giordani & Ruta, 2013): as an example of cross-country tensions in the political debate on internal borders policies, a provocatory tweet of anti-immigrant party FDI leader Giorgia Meloni stated: "Important notice to migrants! France, Germany and Luxembourg have declared that closing ports violates international law and that rescue cannot be criminalized. Head to their *borders*, you will be received with open arms by these welcoming states."[77] Finally, this paper focused on local news and employed standard text-analysis *bag-of-words* methods in the prediction of slant. An important area for future research may involve the exploration of other relevant media and the use of promising, evolving techniques to possibly capture even deeper mappings between text nuances and ideology.

[77] Avviso importante ai migranti! Francia, Germania e Lussemburgo hanno dichiarato che chiudere i porti viola il diritto internazionale e che il soccorso non può essere criminalizzato. Dirigetevi verso le loro frontiere, sarete accolti a braccia aperte da questi Stati accoglienti. Source:*https://twitter.com/giorgiameloni/status/1145015881195540483, posted in June 2019, retrieved in October 2021.*

Appendix

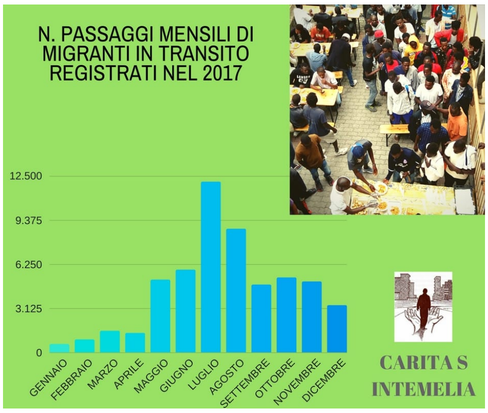
2.A Additional Figures

Figure A.1: Dynamics of the border closure



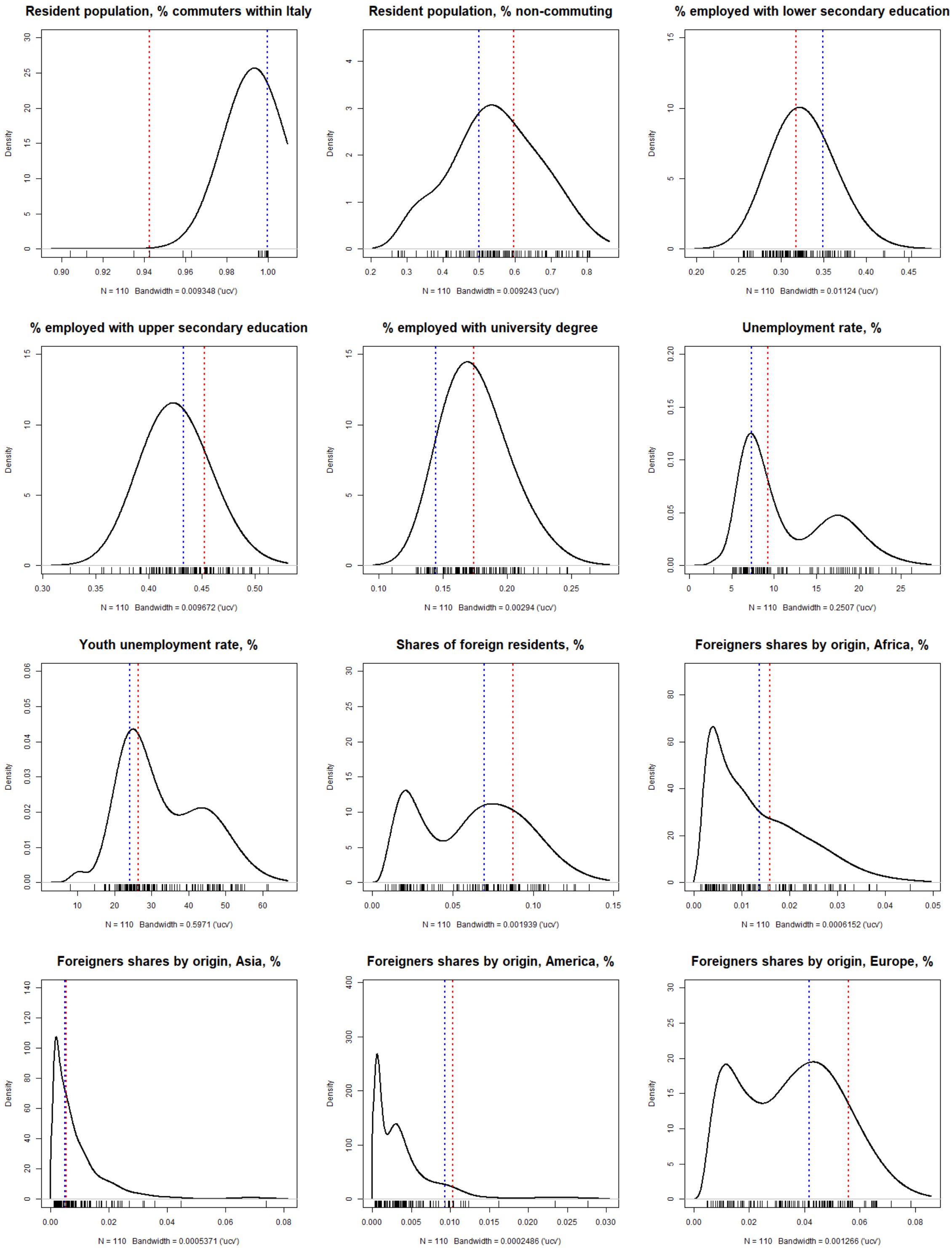
Notes: Figure A.1 depicts the border events. At the left, a timeline summarizes the main occurrences; at the right, a map identifies the area of interest. This image is courtesy of La Cimade (https://www.lacimade.org/).

Figure A.2: Meal counts distributed by Caritas in 2017



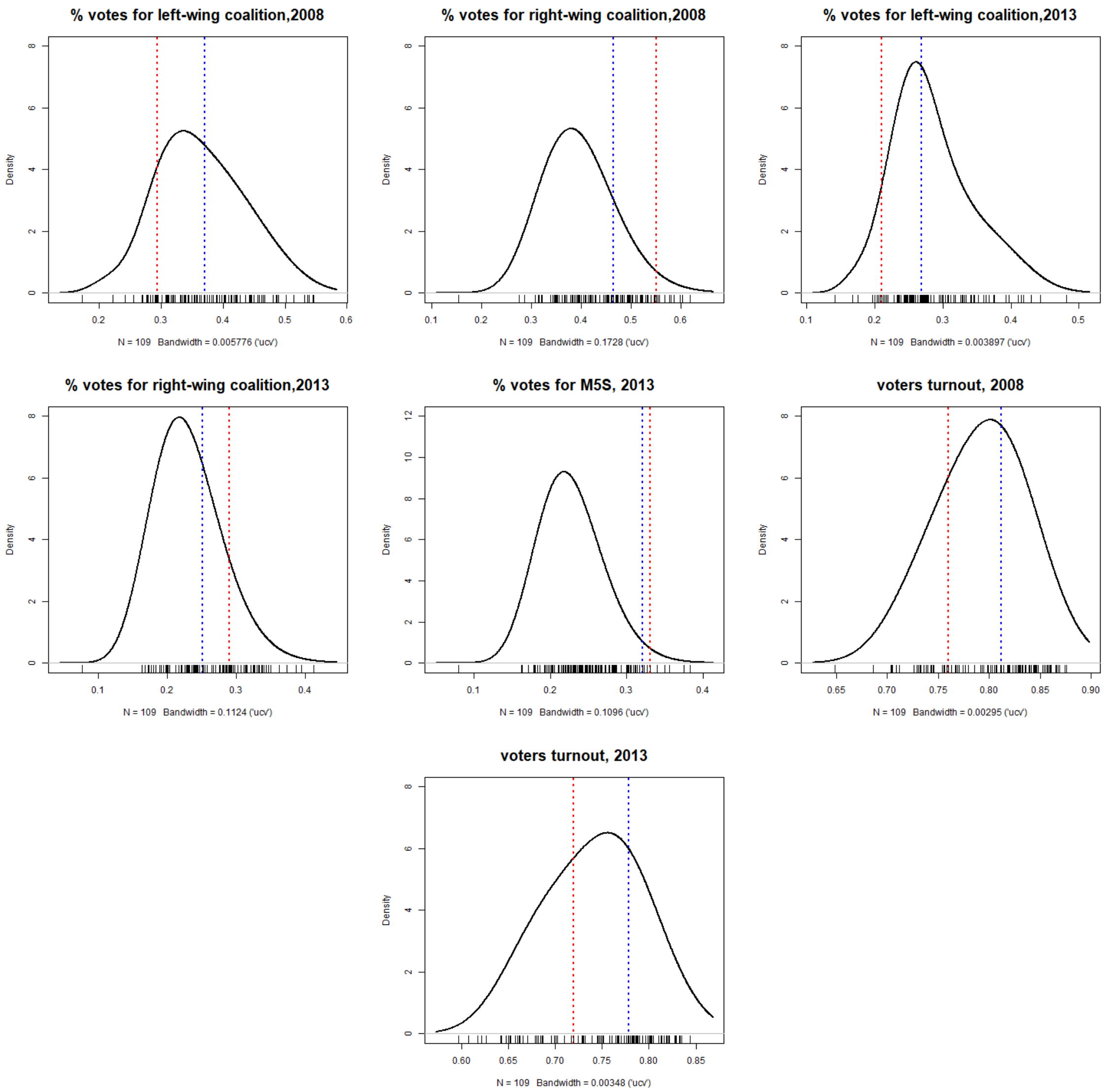
Notes: Stylized statistics on the presence of asylum seekers and migrants that were offered a meal by local NGO Caritas Intemelia. Credits for this graph go to Caritas Intemelia.

Figure A.3: Provinces of interest versus rest of Italy, 2011



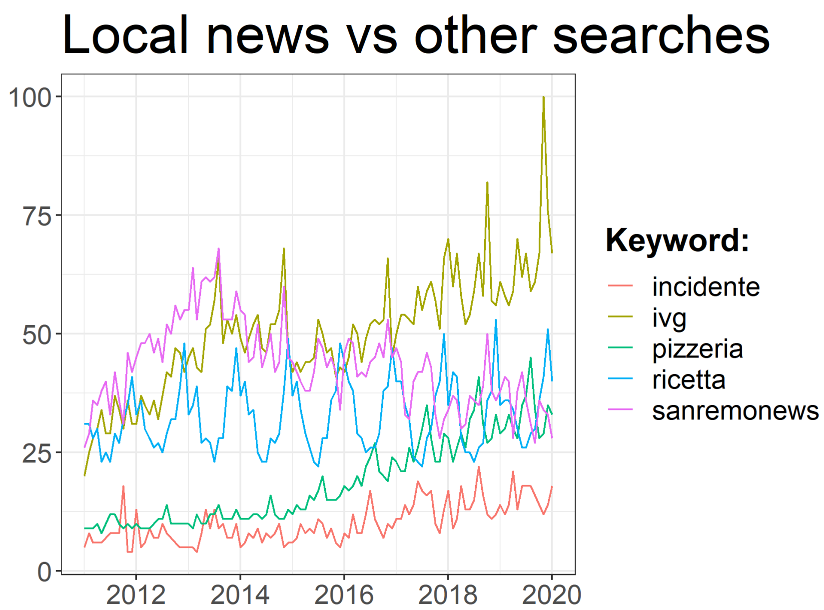
Notes: These graphs show where Imperia (red dotted line) and Savona (blue dotted line) lie within the distribution of Italian provinces on a set of socio-demographic characteristics. Data are sourced from ISTAT, and belong to the Census 2011 dataset. Density graphs are recovered from a univariate kernel density estimation that uses gamma kernel functions as in Chen, 2000, where such kernel choice accounts for the positive range of the data. Bandwidth selection is based on unbiased cross-validation (UCV).

Figure A.4: Provinces of interest versus rest of Italy, continued



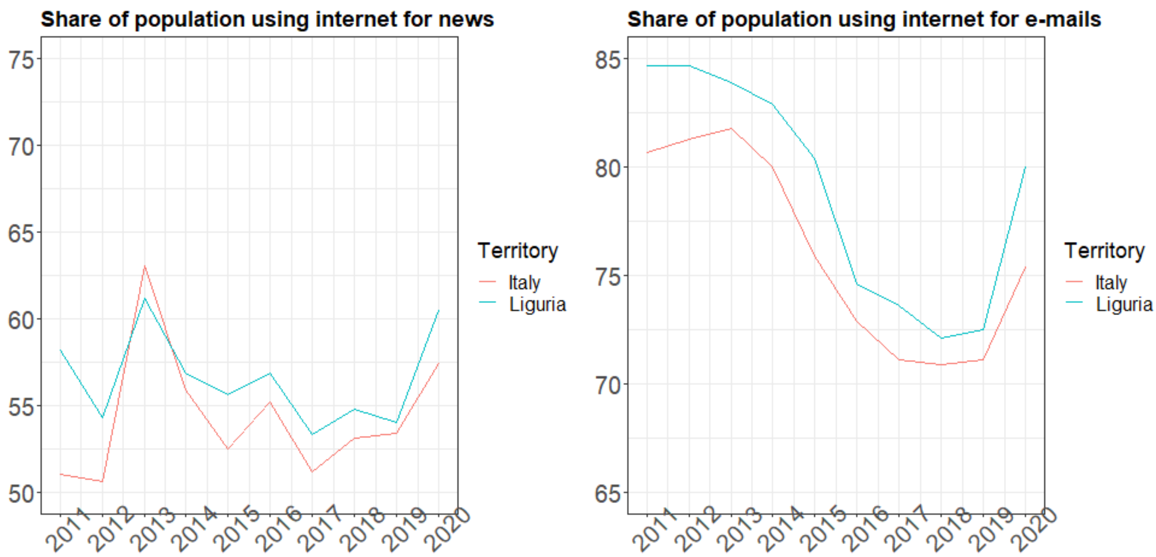
Notes: Continuation of Figure A.3.

Figure A.5: Local news readership



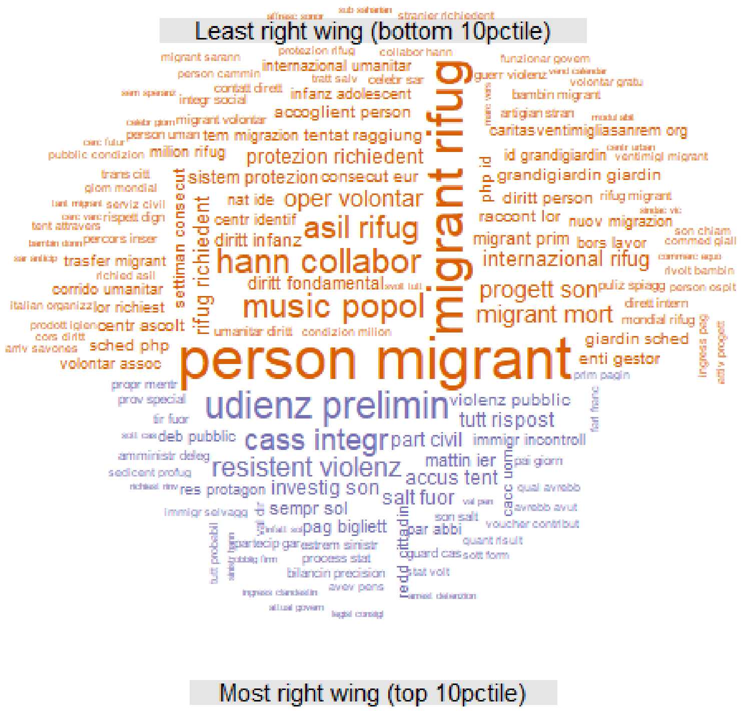
Notes: Comparison of Google searches for two of the main local news outlets, versus other internet searches.

Figure A.6: Internet usage for news consumption



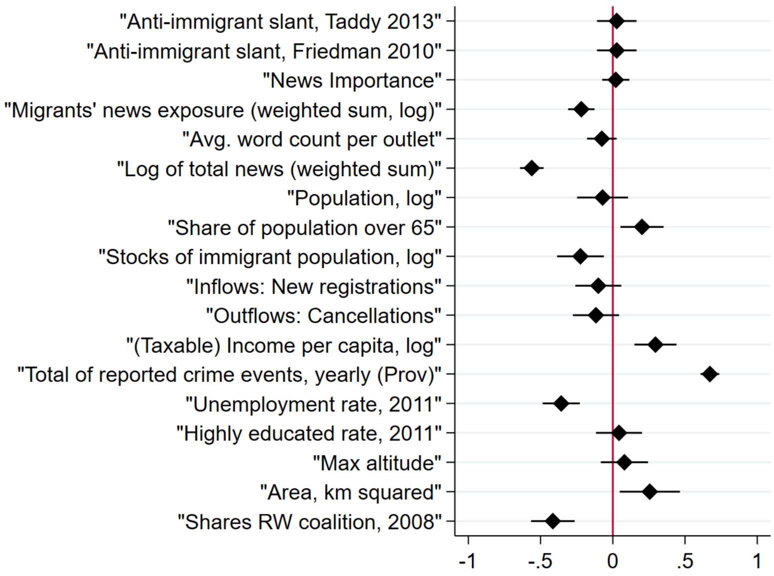
Notes: Share of population that uses internet, sourced by ISTAT. On the left, the share of overall population that uses internet for news. On the right, the proportion of population that uses internet for e-mail.

Figure A.7: Comparison cloud. Terms with highest vs. lowest right-wing affinity



Notes: Exploration of the predictions resulting from the baseline classification approach. Prediction probabilities are employed to subset the sampled articles into least likely (bottom 10% of the assigned probability, at the top, in orange) and most likely (top 10% of the assigned probability, at the bottom, in violet) anti-immigrant.

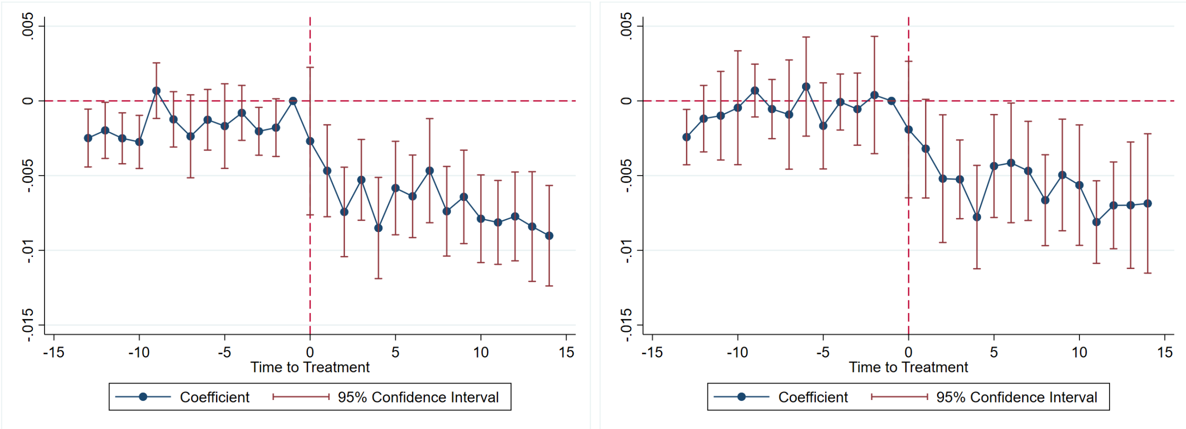
Figure A.8: Balance check



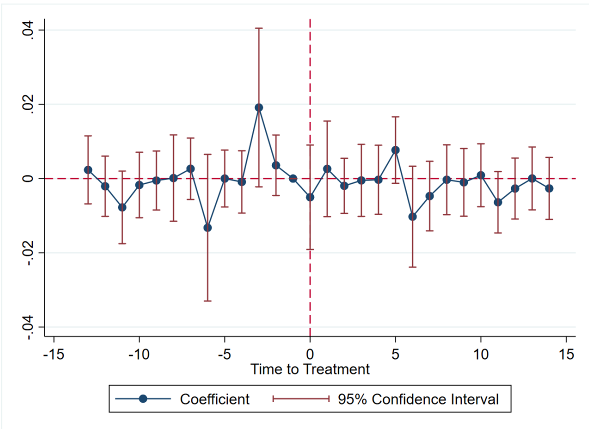
Notes: Balance check: Significance of distance in explaining the pre-June 2015 covariates. Estimates pertain to an OLS estimation of the covariate of interest on commuting distance to the border for the pre-policy subsample, accounting for time fixed effects (except for the census sourced, time-invariant covariates). For comparability, all variables are standardized. Standard errors are two-way clustered: by municipality and month-year.

Figure A.9: Event-study, effect over time.

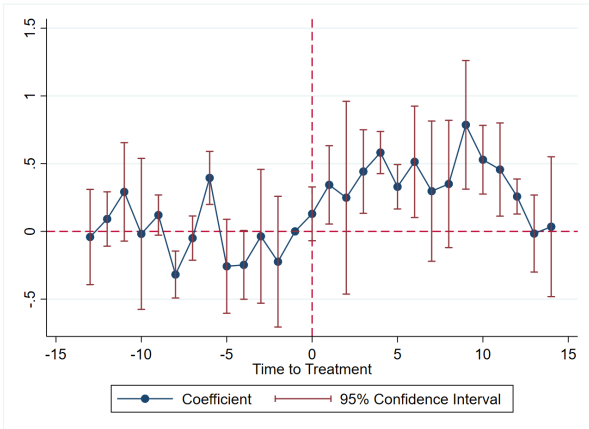
(a) Coverage



(b) Importance

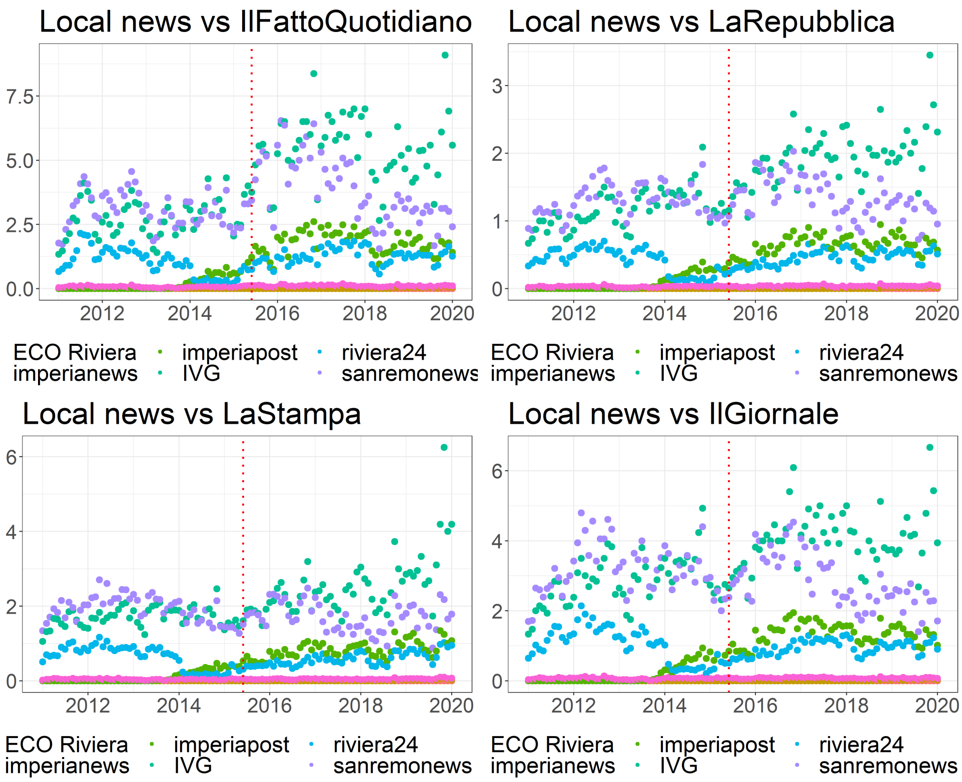


(c) Slant



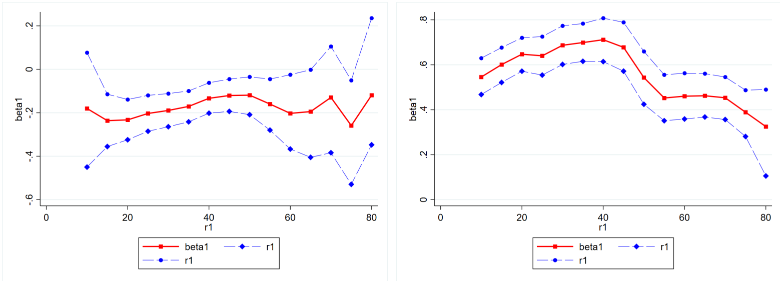
Notes: Coefficients plot from an event-study specification. The outcome of interest is respectively news coverage in subfigure a, news importance in b, and anti-immigrant slant in c. In a, due to the presence of some significant pre-policy coefficients on the left, we also report an alternative specification on the right that controls for an individual linear monthly trend.

Figure A.10: Local news searches vis à vis national news.



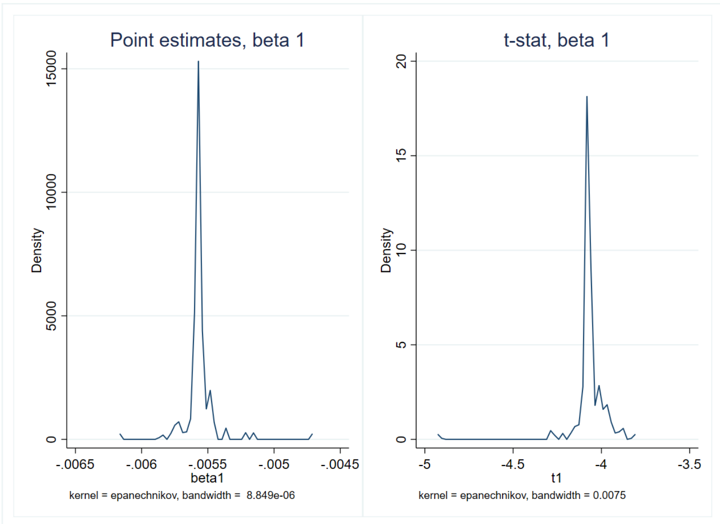
Notes: Proxy for local-news penetration. Values over time. This proxy is calculated as the ratio between internet searches for the national outlet i ($\in$ Il Fatto Quotidiano, La Repubblica, La Stampa, Il Giornale) and local sources *s* (each appearing as different colors in the graphs), as retrieved via the Google Trends platform. Local sources whose Google Trends search did not report any result were assigned a value of zero and do not appear in the graphs.

Figure A.11: β_1 robustness with alternative distance thresholds



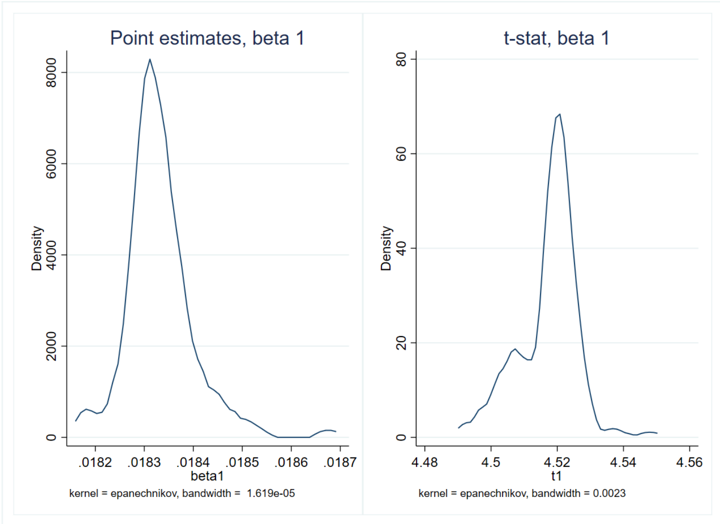
Notes: This figure presents the distribution of estimation results from a alternative specification that considers a binary treatment for distance: on the x-axis the threshold level of commuting distance up to which units are considered to be treated: e.g. for distance=n, treatment is defined as 1 if municipality m is at distance >n. The specifications are comparable to column 4 of the baseline table. Threshold values are plotted on the x-axis and the relative point estimate (red), with 95% confidence interval (blue, dotted lines) constitute the y-coordinates. On the left, graphs pertain to news-coverage. On the right, they refer to anti-immigrant slant estimations. P-values and confidence intervals are obtained with wild cluster-bootstraps based on 2000 repetitions. Clustering is one-way, on panel units.

Figure A.12: Coefficients robustness on news coverage: Leave-one-municipality-out estimates



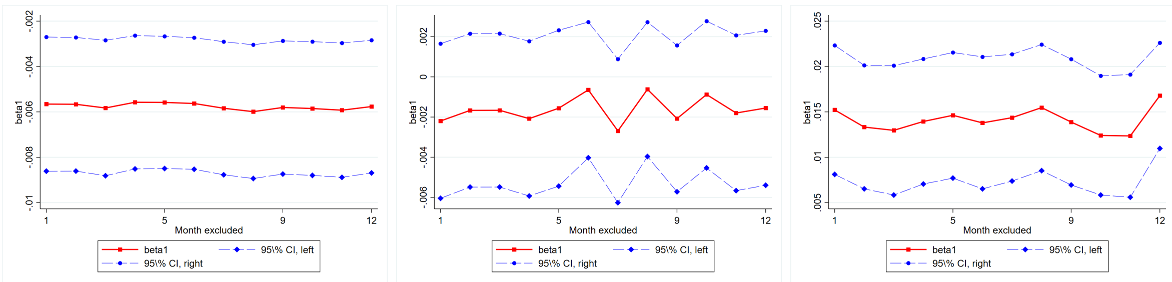
Notes: This figure presents the distribution of estimation results for β_1, where, at each iteration, one municipality is left out of the sample. The reference is the baseline results on news coverage (Table 2.5.1) with the specification including all control variables. In the figure, the left-hand side depicts the distribution of point estimates for β_1. The t-stat distribution for these estimates is on the right.

Figure A.13: Coefficients robustness on anti-immigrant slant: Leave-one-municipality-out estimates



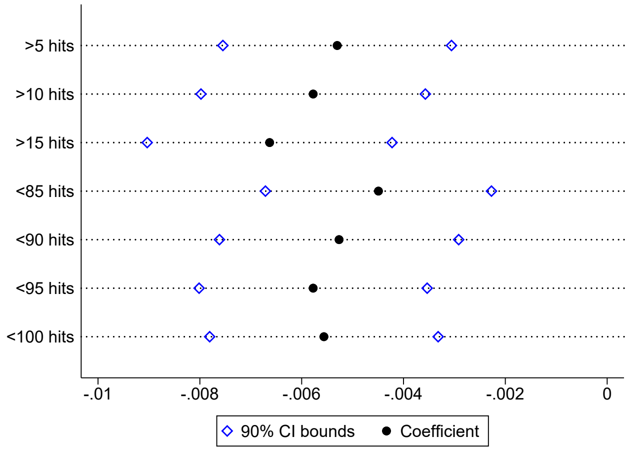
Notes: This figure presents the distribution of estimation results for β_1, where, at each iteration, one municipality is left out of the sample. The reference are baseline results on anti-immigrant slant (Table 2.5.2) with the specification including all control variables. In the figure, the left-hand side depicts the distribution of point estimates for β_1. The t-stat distribution for these estimates is on the right.

Figure A.14: Coefficients robustness: Leave-one-month-out estimates



Notes: This figure presents the distribution of estimation results for the coefficient of interest. At each iteration, one month is left out of the estimation sample. The reference estimates are baseline specifications including all control variables. Threshold values are plotted on the x-axis and the relative point estimate (red), with 95% confidence interval (blue, dotted lines) constitute the y-coordinates. From left to right, graphs pertain respectively to estimations on news coverage, on news importance and on anti-immigrant slant.

Figure A.15: Migration-coverage robustness: Dropping very low, very high hits



Notes: This figure presents regression results from alternative counting of migrant-related news. Each row represents a different regression result for the coefficient of interest, comparable to the baseline estimates (Table 2.5.1, column 4). The rows exclude articles that returned a rating lower than 5, 10, or 15, or higher than 85, 90, 95, or 100, in Google Trends search traffic. 90% confidence bounds are shown in blue, while the point estimates are displayed in black. Their value is on the horizontal axis.

2.B Additional Tables

Table B.1: Further contributions

Study	Setting	Results	Heterogeneity of the results
Dinas et al., 2019	Greece (2012-15)	Municipalities/townships w/ asylum seekers $\implies$ (+) anti-immigrant voting	channels are (-) support for center-right size, (+) turnout.
Campo et al., 2021	Italy (2013-18)	Municipalities w/ asylum seekers centers $\implies$ (+) anti-migrant voting	stronger for (-) municipality size, (+) immigrants' stocks, (-) education level.
Bratti et al., 2020	Italy (2013-18)	(+) proximity to hosting municipalities $\implies$ (+) support for populist parties.	stronger for (-) municipality size,(-) per capita incomes, (-) prior left-wing orientation.
Edo et al., 2019	France (1988-2017)	(+) immigration $\implies$ (+) support for far-right.	Driven by low-educated immigrants from non-Western countries.
Dustmann et al., 2019	Denmark (1986–98)	(+) refugee shares $\implies$ (+) vote for right-leaning, anti-immigration parties.	Urban (weakest /opposite effect) vs rural populations (strongest effect).
Halla et al., 2017	Austria (1970s-2013)	Inflow of immigrants into a community $\implies$ (+) votes for the FPÖ party.	Channel of "compositional amenities". Communities with (+) immigration flows present lower public resources for natives (public daycare, school proximity).
Barone et al., 2016	Italy (2001-2008)	(+) immigration $\implies$ (+) center-right coalition votes.	Effect is heterogeneous by municipality size. Main channels: cultural diversity, labor market competition(education based), public services competition (migrants' fertility), political competition (closeness of votes share of first and second party).
Altındağ and Kaushal, 2020	Turkey(2012–2016)	Syrian-refugee presence produces polarized attitudes towards migrants between Erdoğan's AKP party supporters and opposers.	No impact on AKP voting shares.
Steinmayr, 2021	Upper Austria (2009-2015)	Opposite effects: exposure to asylum seekers $\implies$ (+) far right support; contact (sustained interaction) $\implies$ (-) far-right votes	Qualitative evidence: channel is reduced prejudice after contact.
Otto and Steinhardt, 2014	Hamburg city districts (1987-1998)	Immigration $\implies$ (+) far-right, anti-immigrant voting.	Channels: attitudes are shaped by non-economic determinants and welfare state considerations.
Lonsky, 2021	Finland (2006=2015)	(+) share of foreign citizens in municipalities $\implies$ (-) the Finns Party's vote share by 3.4 percentage points.	Mechanisms:(+) voter turnout. In line with contact theory, results holds only in municipalities with greatest immigration levels.
Gessler et al., 2021	Hungary (2014-2018)	Settlements with highest refugee transit $\implies$ (+) votes against EU refugees quotas (2016 referendum).	Election outcomes suggest vote-share shift from right to far-right. Spillover results show travel distance drastically decreases the effect.
Mayda et al., 2022	US (1990-2010)	(+) share of high-skilled immigrants $\implies$ (-) Republican votes share, vice versa for the low-skilled immigrants.	No heterogeneity of the effects with respect to immigrants' origins. In line with labour market concerns, stronger negative results are found in rural, low-skilled counties.

Notes: Complement to the literature review. This table summarizes a set of contributions on the effect of immigration on attitudes and political preferences of natives.

Table B.2: Summary Statistics

	Mean	Standard Deviation	N	Min	Max
Anti-immigrant slant, Friedman 2010	0.001	1.001	11064	-2.984	3.884
Anti-immigrant slant, Taddy 2013	0.000	1.001	11064	-3.040	3.497
Anti-immigrant slant (predictions)	0.000	1.001	11064	-2.813	2.594
Anti-immigrant slant (predictions), Taddy 2013	0.001	1.001	11064	-3.542	2.960
News Importance	-0.001	1.000	11064	-1.925	3.935
Migrants' news exposure (weighted sum, log)	5.368	0.626	11064	2.833	7.212
Log of total news (weighted sum)	7.607	0.204	11064	7.134	8.312
Avg. word count per outlet	382.300	54.446	11064	239.235	567.256
Population, log	7.159	1.323	11064	4.691	11.032
Population over 65, log	5.903	1.290	11064	3.466	9.789
Population density (population per sq. km)	236.716	343.183	11064	4.759	1922.043
Share of population over 65	0.289	0.051	11064	0.170	0.477
Stocks of immigrant population, log	4.671	1.383	11064	0.000	8.765
Inflows: New registrations	1.713	1.300	11064	0.000	7.650
Outflows: Cancellations	1.674	1.251	11064	0.000	5.832
(Taxable) Income per capita, log	9.952	0.130	11064	9.664	10.723
Commuting distance to Ventimiglia, minutes	45.744	20.072	11064	0.000	83.460
Total of reported crime events, yearly (Prov)	9.470	0.165	11064	9.210	9.740
Unemployment rate, 2011	0.079	0.027	11064	0.013	0.159
Share of university educated, 2011	0.074	0.025	11064	0.025	0.167
Max altitude	955.381	428.416	11064	157.000	2166.000
Area, sq. km	19.981	18.037	11064	1.289	100.658
Total voters, 2008	2369.059	5354.037	11064	67.000	39405.000
Top party is RW, 2008	0.841	0.366	11064	0.000	1.000
Shares LW coalition, 2008	0.322	0.069	11064	0.181	0.544
Top party is RW, 2018	0.425	0.494	11064	0.000	1.000
Shares RW coalition, 2018	0.464	0.068	11064	0.286	0.741

Notes: Summary statistics for the sample of interest.

Table B.3: Extended results: Anti-immigrant slant

	(1) Diff-in-diff, reduced form	(2) Diff-in-diff, reduced form	(3) Diff-in-diff, reduced form	(4) Diff-in-diff, reduced form	(5) Diff-in-diff, reduced form
	Dep. variable: Anti-immigrant slant, Friedman et Al. 2010				
Border distance (min) # Post	0.017***	0.017***	0.017***	0.018***	0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Adjusted R^2	0.77	0.77	0.77	0.77	0.77
	Dep. variable: Anti-immigrant slant, threshold 55				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Adjusted R^2	0.74	0.74	0.74	0.74	0.74
	Dep. variable: Anti-immigrant slant, threshold 45				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.021***	0.021***	0.021***	0.021***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Adjusted R^2	0.78	0.78	0.78	0.78	0.78
	Dep. variable: Anti-immigrant slant, pred. pr., Taddy (2013)				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.022***	0.022***	0.022***	0.022***	0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Adjusted R^2	0.76	0.76	0.76	0.76	0.76
	Dep. variable: Anti-immigrant slant, pred. pr., Friedman et Al. 2010				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.021***	0.022***	0.022***	0.022***	0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	11088	11088	11088	11088	11088
Adjusted R^2	0.78	0.78	0.78	0.78	0.78
Municipality FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes
Population controls		Yes	Yes	Yes	Yes
Migration controls			Yes	Yes	Yes
Income and crime				Yes	Yes
Tot. outlets					Yes

Notes: Extended results for news anti-immigrant slant : results pertain to a reduced form diff-in-diff model outlined in Equation 2.2. The dependent variables vary by section and constitute a variation of the baseline index employed in Table 2.5.2. Standard errors are two-way clustered at municipality and month-year level. Controls are gradually added from left to right. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table B.4: Extended results: Heterogeneity

	News coverage (log)				
	(1)	(2)	(3)	(4)	(5)
	Benchmark results	Education, 2011	LW vote shares, 2008	Altitude (max)	Unemployment rates, 2011
Border distance (min) # Post	-0.006***	-0.004*	-0.004**	-0.007***	-0.005***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Triple Interaction		-0.001	-0.000	0.001*	-0.000
		(0.001)	(0.001)	(0.001)	(0.000)
Adjusted R^2	0.94	0.94	0.94	0.94	0.94
	Anti-immigrant slant				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.018***	0.018***	0.021***	0.020***	0.018***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Triple Interaction		0.000	-0.001*	-0.001*	0.001
		(0.000)	(0.000)	(0.001)	(0.000)
Observations	11088	11088	11088	11088	11004
Adjusted R^2	0.79	0.79	0.79	0.79	0.79
Municipality FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes
Population controls	Yes	Yes	Yes	Yes	Yes
Migration controls	Yes	Yes	Yes	Yes	Yes
Income and crime	Yes	Yes	Yes	Yes	Yes

Notes: Coefficients relate to the dependent variable *news coverage* at the top, and *anti-immigrant slant* at the bottom. The set of controls included is equivalent to Column 4 of the benchmark results. Column 1 is included for comparison and indicates benchmark results. Column 2 allows for an interaction with education levels (as of 2011). Column 3 considers initial political ideology (as from 2008's elections), column 4 and 5 include, respectively, the average altitude of the municipality and the levels of unemployment as of 2011. Standard errors are two-way clustered. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table B.5: Extended results: Distance functional forms

		Log of distance	
	(1)	(2)	(3)
	News coverage (log)	News importance	Anti-immigrant slant
Border distance (min), log # Post	-0.161***	-0.057	0.478***
	(0.031)	(0.045)	(0.132)
Adjusted R^2	0.94	0.95	0.79
		Quadratic distance	
	(1)	(2)	(3)
	News coverage (log)	News importance	Anti-immigrant slant
Border distance, # Post	-0.006	-0.001	0.025***
	(0.005)	(0.002)	(0.005)
Border distance (min), squared # Post	0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)
Observations	11088	11088	11088
Adjusted R^2	0.94	0.95	0.79
Municipality FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
News controls	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes
Population controls	Yes	Yes	Yes
Migration controls	Yes	Yes	Yes
Income and crime	Yes	Yes	Yes

Notes: Extended results, Different functional forms for the distance-based treatment. Results compare to column 4 of the baseline tables 2.5.1 and 2.5.2. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table B.6: Extended results: Time trends at municipality level

	News coverage (log)				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	-0.005**	-0.005**	-0.005**	-0.005**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Adjusted R^2	0.98	0.98	0.98	0.98	0.98
	News importance				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Adjusted R^2	0.95	0.95	0.95	0.95	0.95
	Anti-immigrant slant				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.020**	0.020**	0.020**	0.020**	0.019**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	11088	11088	11088	11088	11088
Adjusted R^2	0.80	0.80	0.80	0.80	0.80
Municipality FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
Municipality time trends	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes
Population controls		Yes	Yes	Yes	Yes
Migration controls			Yes	Yes	Yes
Income and crime				Yes	Yes
Tot. outlets					Yes

Notes: Extended results, linear time trends interacted with municipality dummies. The table structure is comparable to the baseline estimates. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table B.7: Robustness to the exclusion of the imputed sample

	Dep. variable: News coverage (log)				
	(1) Diff-in-diff, reduced form	(2) Diff-in-diff, reduced form	(3) Diff-in-diff, reduced form	(4) Diff-in-diff, reduced form	(5) Diff-in-diff, reduced form
Border distance (min) # Post	-0.002	-0.001	-0.002	-0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.95	0.95	0.95	0.96	0.96
	Dep. variable: News importance				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.94	0.94	0.94	0.94	0.94
	Dep. variable: Anti-immigrant slant				
	(1)	(2)	(3)	(4)	(5)
Border distance (min) # Post	0.020***	0.020***	0.020***	0.019***	0.019***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	2987	2987	2987	2987	2987
Adjusted R^2	0.78	0.78	0.78	0.79	0.79
Municipality FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes
Population controls		Yes	Yes	Yes	Yes
Migration controls			Yes	Yes	Yes
Income and crime				Yes	Yes
Tot. outlets					Yes

Notes: Robustness test of the main results against the use of the non-imputed sample only. The dependent variables are the three media outcomes of interest. Standard errors are two-way clustered at municipality and month-year level. Controls are gradually added from left to right. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table B.8: Extended results: Placebo predictions for slant

	Dependent variable: Anti-immigrant slant				
	(1)	(2)	(3)	(4)	(5)
Border distance (min)					
# Post	0.004	0.004	0.004	0.004	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	11088	11088	11088	11088	11088
Adjusted R^2	0.69	0.69	0.69	0.69	0.69
Municipality FE	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes
News controls	Yes	Yes	Yes	Yes	Yes
Months to elections	Yes	Yes	Yes	Yes	Yes
Population controls		Yes	Yes	Yes	Yes
Migration controls			Yes	Yes	Yes
Income and crime				Yes	Yes
Tot. outlets					Yes

Notes: Extended results, baseline estimates are tested to the use of a placebo outcome, created by applying the slant classification algorithm to a training sample where 0 and 1 labels are shuffled randomly. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

2.C The Political Context in Italy

As of 2021, Italy is formed by 7,904 municipalities (source: ISTAT), which constitute the lowest level of government. Municipalities are organized in 107 territorial bodies which correspond to 83 provinces, 14 metropolitan areas and 10 otherwise denominated entities, with an equivalent broad role. Provinces are then grouped into 20 regions. At the national level, the Italian Parliament is bicameral, composed of the Chamber of Deputies and Senate of the Republic. Elections of their members are held every five years.

The recent Italian political landscape is rooted in a major political crisis in the early 90s, caused by a series of scandals that were famously termed *Tangentopoli* (Bribeville). A set of investigations uncovered extensive corruption systems that implicated entrepreneurs and politicians in power, for both major political parties at the time (the Italian Socialist Party and the Christian Democrats). In this setting, the entrepreneur Berlusconi, although involved in some connected investigations, gained influence and formed a center-right coalition which allowed him to become the Prime Minister for the first time in 1994. This set of scandals marked the end of the so-called *First Republic* and the beginning of the *Second Republic* in 1994, which period saw the rise of a bipolar setting with two major coalitions: the center-left and center-right. Several authors mark the 2013 elections as defining the end of this Second Republic (D'Alimonte, 2013; Durante et al., 2019; Tebaldi, 2014). In 2013 in particular, comedian Beppe Grillo brought his newly created Five Stars Movement to the elections, obtaining an unanticipated, relative success. Five Star gained significant traction among an unsatisfied, unrepresented electorate, and internet diffusion was found to have a major role (Campante et al., 2018). This political movement is generally associated with a broadly populist stance (Bratti et al., 2020; Campo et al., 2021). Within this scenario, and with the migration crisis peaking in 2014-2015, Italy saw the rise of two right-wing parties that maintained a strong nativist, anti-immigrant rhetoric (Bratti et al., 2020; Campo et al., 2021; Gamalerio, 2018; Romarri, 2020): Lega and Fratelli d'Italia (FDI).

Lega's party was founded in 1991 as Lega Nord and was originally a separatist party that broadly aimed at a secession of the more productive Northern Italy from the Center-South and therefore supported political and fiscal federalism. In the 1992's general elections, the party obtained a vote share of around 8%. More recently, in the 2013 general elections, it joined Berlusconi's coalition, and obtained little above 4% in each of the two chambers. After the 2013 elections, Matteo Salvini assumed leadership of the party and abandoned the Northist stance and maintaining a strong anti-immigrant rhetoric. Lega's Manifesto of 2018 expressly takes a stand against the NGO operators in the Mediterranean Sea and maintains that immigration should be based on cultural proximity. Salvini's party obtained well above 17% of the vote in the 2018 general elections.

Fratelli d'Italia is a nationalist party that emerged in 2012 with a separation from the center-right coalition. It has been led by Giorgia Meloni since 2014, it has a conservativist, nationalist ideology of post-fascist inspiration. It takes a well-defined anti-receptionist position with a strong anti-islamic rhetoric. FDI had been part of the same center-right coalition as Lega in the 2013 general elections. While failing to reach a 2% vote share in the 2013, 2018's general elections saw the party's electorate increase more than two fold, exceeding 4% of the vote.

2.D Geocoding News

Key to the empirical strategy of this paper, each local news outlet considered must be assigned to a local area it serves. Online newspapers are in principle readable by anyone regardless of their locations, but local outlets tend to provide content on traffic, events, and advertisements specific to a particular area they establish to cover. Coverage data are not directly available: we do not observe individuals' consumption of local news in the sample of interest. Google Trends serves as a proxy to circumvent this issue, as it provides data on how specific terms are searched on Google by municipality. Using this information, exposure to local news for each municipality is approximated with a two-steps procedure.

1. Google Trends is used to obtain search metrics for each news source across municipalities. It provides:
   i) a rating of users' traffic *by municipality*, scaled from 1 to 100, *given a time-*

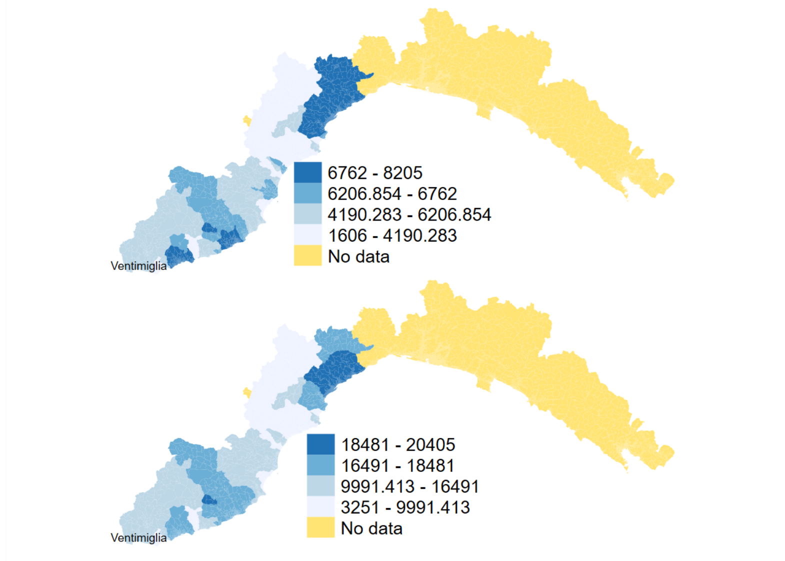
range. The platform normalizes search results by location and time range to avoid artificially giving too much weight to areas with overall high search volume. The resulting scaled outcome is therefore a measure relative to all searches on all topics.[78]. There are two alternative time-ranges considered: January 2011-January 2015 and June 2015-January 2020. A broad enough time-range allows Google Trends to provide more uncensored information for municipalities with less traffic. In fact, the narrower the time interval, the less detailed data are on the platform, given that it does not display information below a minimum search-traffic rate. For example, *Sanremonews* was mostly searched in the municipalities of Taggia (Google Trends rating =100) and Sanremo (Google Trends rating =75) for the 2011-2015 period. Let this resulting metrics be called $rank1_{ism\tau}$: the Google Trends' rating of source s over the sum of all s for m, $\tau \in \{2010-2015; 2015-2020\}$. Figures D.2 and D.3 show Google Trends search results for the sources with most search traffic, in the time-ranges 2010-2015 and 2015-2020, respectively.
ii) To allow for more granular time-variation, data on source traffic over time *for the whole region* is retrieved, using a benchmark source for reference (the sample source IVG is used as reference, reaching the highest relative traffic in the series period). For each month-year period, the traffic for a source is rated again on a scale of 1-100. The resulting cross-time metric is $rank2_{ismt}$, i.e., the Google Trends rating of source s at month-year t.
Importantly, news sources with less traffic did not return municipality level information from Google Trends. Their weight is zero in the benchmark analysis.
To recap, i) varies by municipality and ii) varies by time (month-year). Combining this information, the weight of article i for municipality m will be the product of i) its importance returned by the cross-municipality rating and ii) its importance returned by the time-varying rating. Weights are normalized to add up to 1 for every panel-month-year unit. More precisely: the *weight* w_{ismt} of article i, published in source s, for municipality m, month-year t equals $w_{ismt\tau} = \frac{rank1_{ism\tau} * rank2_{ismt}}{\sum_{i \in m,t}(rank1_{ism\tau} * rank2_{ismt})}$.

2. In a second step, a simple imputation method expands on the initial proxy to a set of municipalities not appearing in Google Trends. Municipality m_1's information is imputed from its nearest neighbor municipality m_2, where neighborhood is established based on commuting patterns. Data on commuting patterns at municipality level for 2011 is sourced by ISTAT, with information on how many individuals residing in municipality m_1 commute to work or study in municipality m_2. If the percentage of commuters among the residents is less than 25%, data are not imputed.[79] Otherwise, information for municipality

[78] https://support.google.com/trends/answer/4365533?hl=en
[79] The rationale is that the higher the level of commuters, the more likely the news at the commuting destination may reach the commuters.

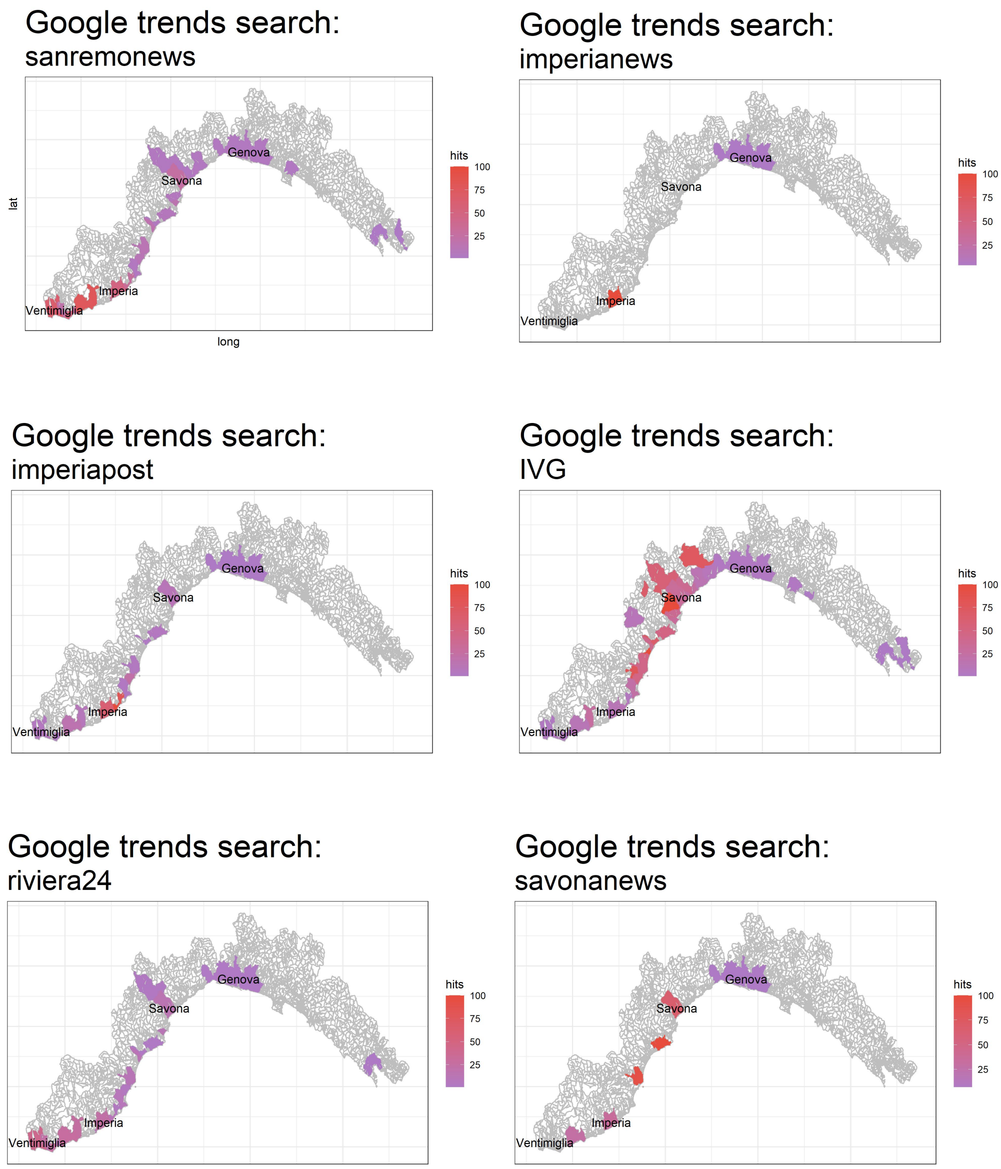
m_1 is proxied with the average across commuting destinations $m_k \in K$, where the set K is such that the difference between the share of all commuters and the share of commuters for which data on m_k is available is no more than 20%. Information for m_1 is imputed as the weighted average of information from observed js, where importance weights are the commuting shares. This procedure is reiterated and leads to data as in Figure D.1. Table F.1 lists all 132 municipalities for which news data has been geo-localized in both the periods before and after June 2015.

Figure D.1: News sample geographic distribution, before and after June 2015



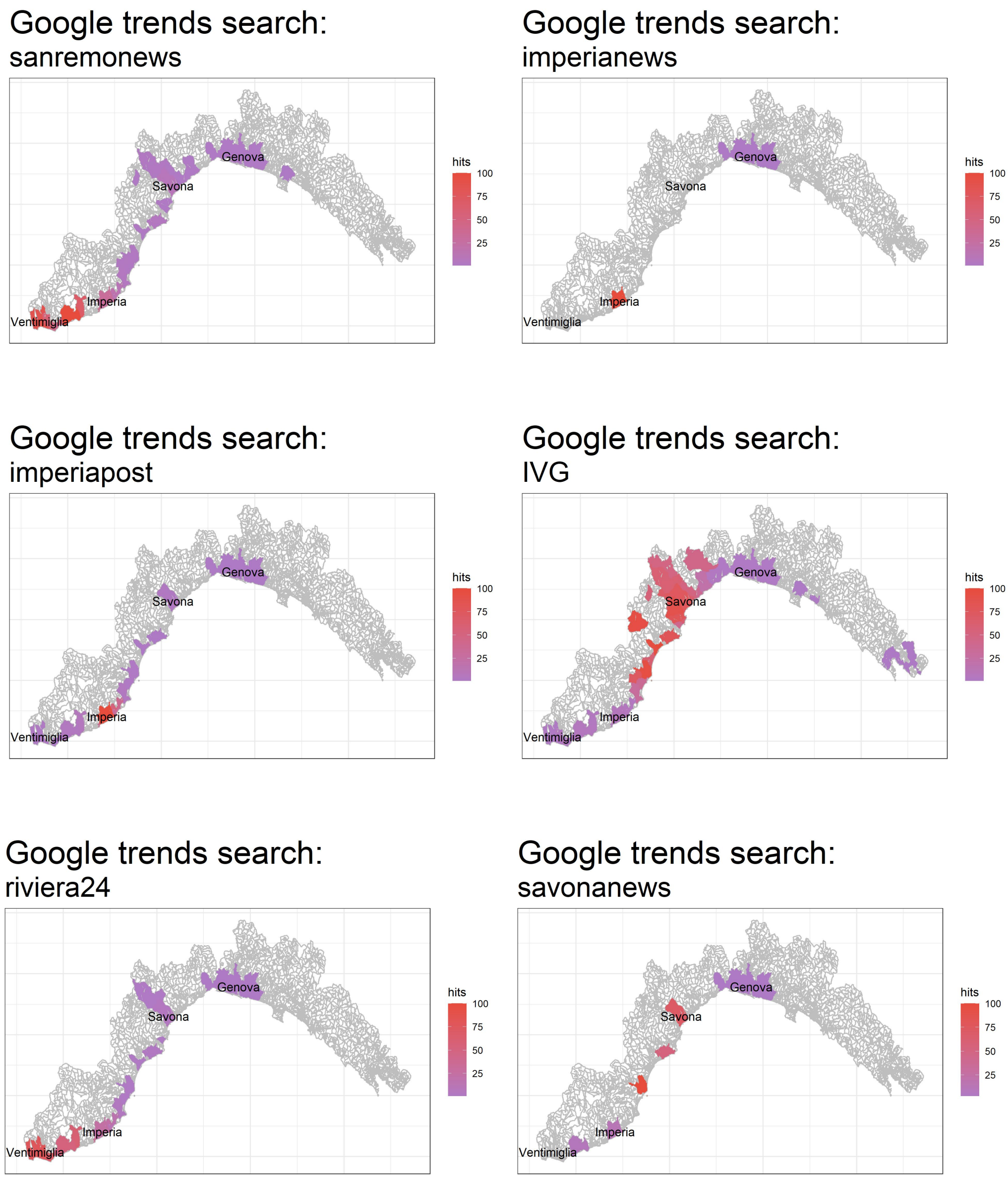
Notes: Data visualization of the news sample. On the top map are data related to the pre-treatment period, while the post treatment period is illustrated on the bottom. News coverage patterns result from the geo-localization process described in the paragraph and pertain to the provinces of Imperia and Savona, which are respectively the closest and second closest provinces to the French border in the region of Liguria.

Figure D.2: Local news sources, Google trends data. Pre-treatment



Notes: Local news sources and geographic interest of users, based on Google Trends data for the period ranging 2010 to 2015.

Figure D.3: Local news sources, Google Trends data. Post-treatment



Notes: Local news sources and geographic interest of users, based on Google trends data for the period ranging June 2015 to 2020.

2.E Text-Based Measures

News Importance

By drawing a parallel from Kelly et al., 2021's index of patent importance, a measure of news importance is constructed as the ratio of two indices: a novelty measure and a measure of impactfulness. Both these indicators are built given text similarities of the articles in the sample, where similarity is a function of term frequencies in the texts. The original measure is applied by Kelly et al., 2021 in the patent literature, as a new indicator of patent quality. Higher quality for patents is described as greater novelty-low similarity with previously published patents-and greater impactfulness-high similarity with future patents. This text-based measure for patents was observed to correlate strongly with market value indicators, which the authors interpret as a sign of high reliability. Closely following this patent-related approach, the same measure is constructed in this study, where, instead of patents, the corpus of text is constituted by news.

In this way, the evolution of news content can be explored over time and across distance levels. The end goal is investigating whether and how novel and impactful content spread as a consequence of the border policy. The only divergence from Kelly et al., 2021 here involves the time frequency, as this setting adopts smaller time spans, to accommodate the higher frequency of news publications, relative to patents. Importantly, the development of this metric involves first building pairwise similarity values between each pair of documents, and second aggregating these values into a document-level index.

In an NxM matrix of documents $i \in \{1, ...N\}$ and terms $j \in \{1, ...M\}$, the term-frequency, inverse document-frequency is defined as

$$tf - idf_{ij} = tf_{ij} \times idf_{ij} \tag{2.5}$$

A higher $tf - idf_{ij}$ level indicates that term j is generally frequent in document i, but is not very much frequent in most other documents, thus suggesting it is an informative term for the document's content.

In the alternative version presented by Kelly et al., 2021, time dimensionality is introduced in this indicator, and the *backward-idf* is defined as the ratio between log frequency of all documents dated before document i, over the log frequency of all these prior documents that contain term j. Time is considered here at month-year level.

$$Bidf_{ij} = \frac{log(\text{number of documents prior to } i)}{log(1 + \text{number of documents prior to } i \text{ containing term } j)} \tag{2.6}$$

This measure thus represents the history of the term frequency up to the time of document i. Given documents' pair $(i; i')$, their similarity will be based on the following modified $tf - idf$:

$$tf - Bidf_{ijt} = tf_{ij} \times Bidf_{ijt} \text{ where } t = min(t_i, t_{i'}) \tag{2.7}$$

Vector $tf - Bidf_{it}$ will then have size W equal to the set of terms j present in both i and i'. This vector is normalized to have unit length, and proximity between i and i' is measured by cosine similarity. This computation is typically used in unsupervised learning clustering methods such as spherical K-means. Compared to other proximity measures, such as the Euclidean distance, cosine similarity is conveniently independent of document length and corresponds to the dot product between the two normalized vectors. It ranges between 0 and 1, 0 occurring when documents have no overlapping terms and 1 when two documents use the same words in the same proportion.

$$\text{Cosine similarity}_{i,i'} = \rho_{i,i'} = \frac{tf - Bidf_{it}}{||tf - Bidf_{it}||} . \frac{tf - Bidf_{i't}}{||tf - Bidf_{i't}||} \tag{2.8}$$

It is important to stress that the sample of interest contains news as old as 2010, and that the time unit considered is the month-year. For each of these metrics, a sliding window is constructed such that for month-year *t*, articles dating at most one year prior (i.e., *t*-12) and at most one year after (i.e., *t*+12) are employed. With this methodology, measuring similarity at time *t* requires lagged data availability. For this reason, the first month-year for which this indicator is available for analysis is January 2012, as the previous 12 months will be used as lags in the measure construction. Similarly, data on this index would end in 2018, as 2019 data are used as leads in the construction. Kelly et al., 2021 define *novel* patents as those whose content is most distinct from their predecessors, meaning they rely less on existing contributions. In the context of news, an article featuring novel content will be less similar to previous discourse. *Backward similarity* is defined as:

$$\text{BS}_{i',12} = \sum_{i \in \boldsymbol{B}_{i',12}} \rho_{i,i'} \tag{2.9}$$

Where $\boldsymbol{B}_{i',12}$ denotes the set of documents

dating prior to i', given a maximum of T=12 lags considered. *Impactful* news items are those that are most influential, which would be reflected in sharing content with future content. In this sense, *Forward similarity* is defined as:

$$\text{FS}_{i',12} = \sum_{i \in \boldsymbol{F}_{i',12}} \rho_{i,i'} \tag{2.10}$$

Where $\boldsymbol{F}_{i',12}$ denotes the set of documents

dating posterior to i', given a maximum of T=12 leads considered. Finally, news importance $q_{i'}$combines forward and backward similarity to identify novel and impactful news:

$$q_{i'} = \frac{\text{FS}_{i',12}}{1 + \text{BS}_{i',12}} \tag{2.11}$$

Which is equivalent to a ratio of *forward similarity* over *backward similarity*[80]. Figure 2.4.2 represents the evolution over time of the three computed measures: novelty, impactfulness (on the left) and importance (on the right). The red line displayed in the graph defines the periods before and after June 2015. As an interesting visual pattern, both similarity measures feature higher levels in the post period. A peak in news importance appears during the month of June 2015.

[80] Adding 1 to avoid having zero at the denominator

This higher level is suggestive of the reliability of this measure in identifying unprecedented shocks in news content.

Media Slant

Among the prominent contributions in text-based measures of media slant, Groseclose and Milyo, 2005 constitute a seminal example. The authors use US Congressional citations to estimate the political positions of think tanks, and then use their mentions to predict media partisanship in twenty news outlets. Gentzkow and Shapiro, 2010 build on this method and obtain media slant indices for 433 outlets, by enlarging the set of terms from sole think tank citations, to a broader set of text occurrences, selected in terms of relevance via a χ^2 statistic. Given this feature selection, the authors predict slant via a two-step supervised generative model. The broad idea behind Groseclose and Milyo, 2005 and Gentzkow and Shapiro, 2010 is to use text issued from politicians' discourse, whose affiliation is known, as a *training set* to predict the ideology of newspapers, unknown a priori but inferable from how similar it is to the political speeches. More recently, Taddy, 2013 improves on these methodologies by proposing a model in which a multinomial inverse regression reduces the dimensionality of the predictors (terms) to a univariate score. A *forward regression* step then predicts the response (slant labels in this context), given this reduced information. In this application, Taddy, 2013 is benchmarked against an alternative elastic-net penalized logistic regression (Friedman et al., 2009; Friedman et al., 2010) and found to perform slightly better in a validation step. To construct the training set, this study relies on a set of four news sources whose slant (or lack thereof) is taken as evident. This constitutes a difference from Groseclose and Milyo, 2005 and Gentzkow and Shapiro, 2010, who employ politicians' speeches as their predetermined, labeled sample. Employing news to train the model guarantees that they belong to the same journalistic dimension as the unlabeled, target news set. Other than this comparability argument, a motivation for this choice is data availability. Use of Italian political speeches would present data limitation, further complicated by the complexity of a fractionalized political scenario that does not directly reduce to the more tractable bipolar *Democrats-Republicans* setting adopted in the US studies. A discussion of the Italian political landscape is detailed in appendix 2.C.

The classification proposed here involves the construction of a simple binary variable, where a value of 1 corresponds to bias toward anti-immigrant discourse and 0 to the lack of it. The *training sample* is constructed as follows.

Anti-immigrant labeled news items in the training sample derive from national newspapers *La Verità* and *Il Giornale*. The former outlet was founded in 2016 and openly takes an anti-immigrant stand. This is documented, for instance, in the online section discussing the migration crisis context, entitled *Chronicles of*

Invasion (it. Cronache dell'Invasione). According to survey statistics diffused by the market research platform YouGov,[81] this news outlet is considered right-wing by 81% of respondents. Of these, 17% classify it as far-right, the highest percentage among all news outlets considered by the researchers. 12% of people classify it as center oriented or non-oriented, while the remainder considers it a left-wing source. Data from *La Verità* are collected from its online platform by considering all news that is included into the *Chronicles of Invasion (it. Cronache dell'Invasione)* section, and complement this extraction with migrant-related news by a similar keywords-search fashion as for my main dataset. The latter source *Il Giornale* shares similar YouGov statistics to *La Verità* and also takes an evidently critical rethoric against migration.[82] Data from the *Il Giornale* are collected from the online platform by considering all news from the same keyword searches used for the local news sample. These news articles take label value 1.

Non right-wing labeled news in the training sample derive from two sources. One is the website *L'Unità news*, self-defined as a not-for-profit news aggregator of *antifascist and anti-racist information*. The website also hosts the archives for and shares the name with the discontinued newspaper *L'Unità* founded by Antonio Gramsci in 1924 as the official news outlet for the Italian Communist Party. News published in this online platform are extracted, following the keywords-search fashion as for the main dataset. The second source is the online version of regional newspaper *Il Secolo XIX*. This outlet was founded in Genova, Liguria in 1886. Since 2015, the outlet had been affiliated with the national source *La Stampa* and since 2017 is part of editorial group GEDI, which includes, among others, the daily *La Repubblica* and the weekly *L'Espresso*.[83]. News collection for *Il Secolo XIX* follows the same keyword-based steps. Articles coming from these two sources are labeled with a 0 in the binary slant measure.

Via this procedure, the training set is constituted by 5926 0-labeled and 5293 1-labeled instances, which will serve to classify the main news dataset. This study proposes two classification approaches: i) a penalized maximum likelihood logistic model with elastic-net regularization (Friedman et al., 2010; Zou & Hastie, 2005), with 10-fold cross-validated tuning parameters λ (the penalty parameter) and α (the level of mixing between lasso and ridge, with $\alpha = 1 \implies$ full lasso). This is compared with ii) the alternative Taddy, 2013's methodology.[84]

For every article in the training set, a document-term matrix is constructed as described in section 2.4.2, with rows constituting the training set articles i and

[81] https://it.yougov.com/news/2019/05/03/giornata-mondiale-della-liberta-di-stampa/

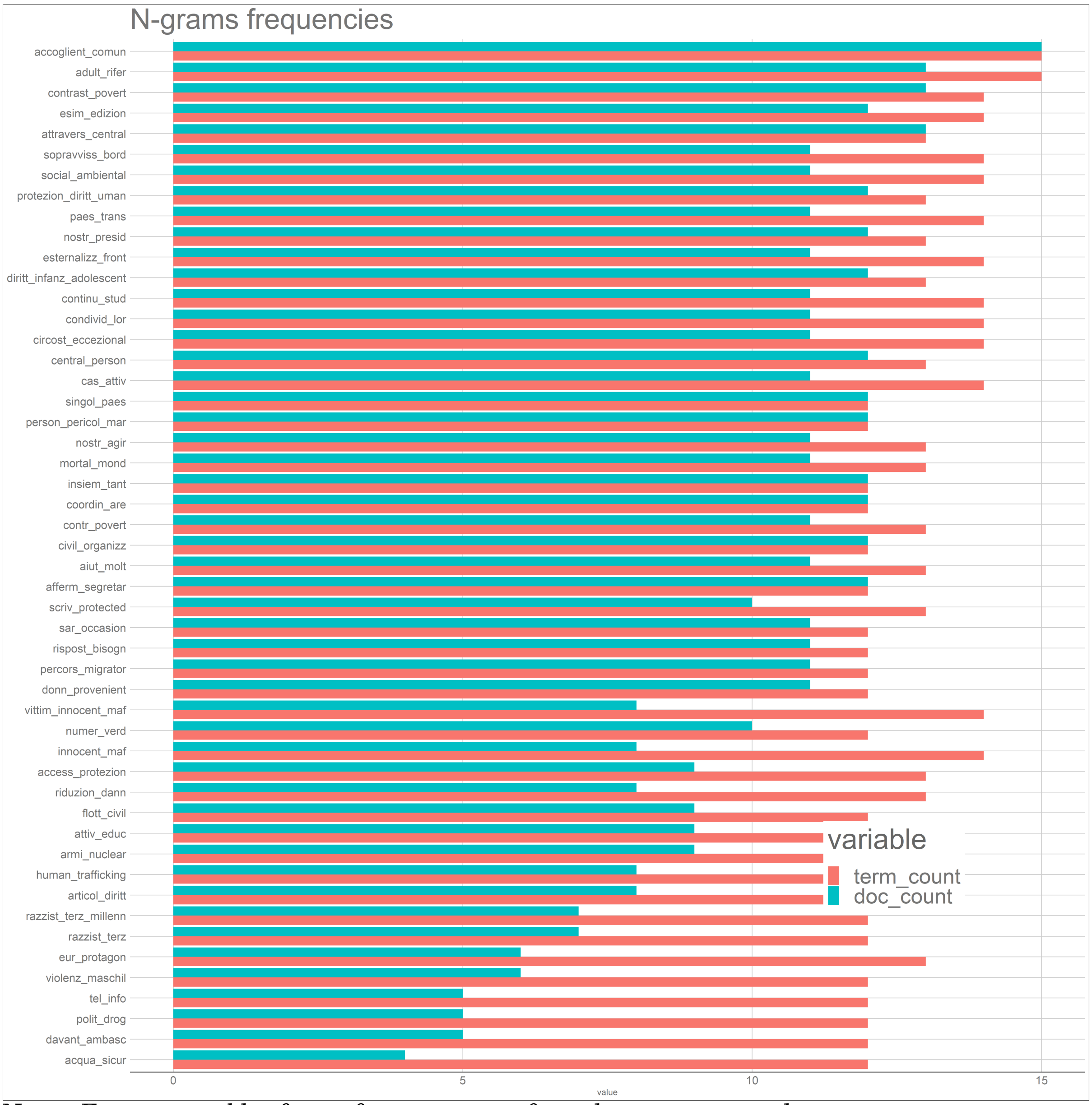
[82] An headline example from February 2022: *https://www.ilgiornale.it/news/politica/carola-leroina-fuori-legge-2007541.html*: "Carola Rackete, the hero of the radical-chic, rightwing world, reveals that she was even more Taliban than the reception of the German NGO Sea Watch."

[83] According to the aforementioned YouGov report, La Stampa is perceived as center-oriented by 33% of respondents and left-wing by 39%. La Repubblica is considered left-wing leaning by 79% of the interviewed.

[84] The two measures share the same prediction in roughly 86.7% of instances.

columns constituting the n-grams j (n$\in 2,3$) present in the articles. Preprocessing steps are performed via the R package *text2vec*[85]. The vocabulary of n-grams is pruned via a feature-selection based on the χ^2 statistic of Gentzkow and Shapiro, 2010. For an idea of the matrix content, Figure E.1 summarizes the frequencies of some top frequent n-grams.

Figure E.1: Document-term matrix, sample of frequent terms.



Notes: Frequency table of most frequent terms from the training sample.

In Friedman et al., 2010's method, the document-term matrix cells will contain the metric $tf - idf_{ij}$. the objective function for logistic regression[86] is the penalized

[85] https://CRAN.R-project.org/package=text2vec

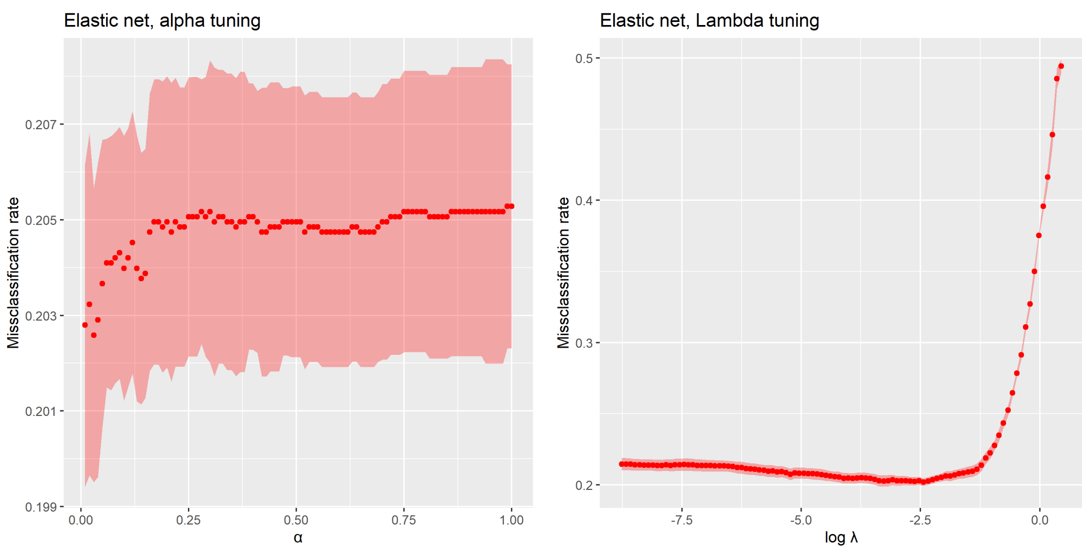
[86] Given an observed binary outcome $Y \in 0,1$, the logistic model can be written as $\frac{p(Y=1|X=x)}{p(Y=0|X=x)} = \beta_0 + x^T\beta$.

negative binomial log-likelihood function, given N sample size and p parameters:

$$min_{(\beta_0,\beta)\in R^{p+1}} - [\frac{1}{N}\sum_{i=1}^{N} y_i(\beta_0 + x_i^T\beta) - log(1+e^{(\beta_0+x_i^T\beta)})] + \lambda[(1-\alpha)||\beta||_2^2/2 + \alpha||\beta||_1] \quad \textbf{(2.12)}$$

On the right, the penalty severity is determined by the tuning parameter λ. This regularization is a convenient approach for models with a high number of parameters, which may suffer from over-fitting problems. The elastic-net mixes between two penalty functions: the ridge-regression penalty (α = 0) and the lasso-regression penalty (α= 1). The motivation behind this mixing lies on the aim to exploit the qualities of each approach, while overcoming their limitations if considered singularly. lasso allows for a better parsimony of the model as it shrinks some parameters to zero. In case of high correlations between predictors, however, lasso may omit relevant information, as would only select one coefficient, ignoring the rest. Friedman et al., 2010 suggest that $\alpha = 1 - \epsilon$ for small $\epsilon > 0$ may already be a convenient solution to avoid lasso degeneracies and conserve its sparsity property. In this study, hyper-parameters λ and α are chosen from a 10-fold cross-validation procedure on the training sample. Figure E.2 displays the levels of α (on the left) and λ (on the right) that minimize the missclassification rate (on the y axis).

Figure E.2: Tuning parameters for the Elastic net.



Notes: Cross-validation results. Tuning parameters appear on the x-axes. On the left, α constitutes the level of mixing between lasso and ridge. On the right, λ constitutes the severity of the penalty component. On the y-axis, the missclassification rate is used as a measure of prediction quality.

The binary classification procedure returns probability scores, where a probability corresponds to the estimated degree of likelihood that the article is labeled as 1 (= right-wing). In the benchmark, for a probability score higher than 0.5, the article is assigned the value 1 (some variation on this threshold is considered in the extended results).

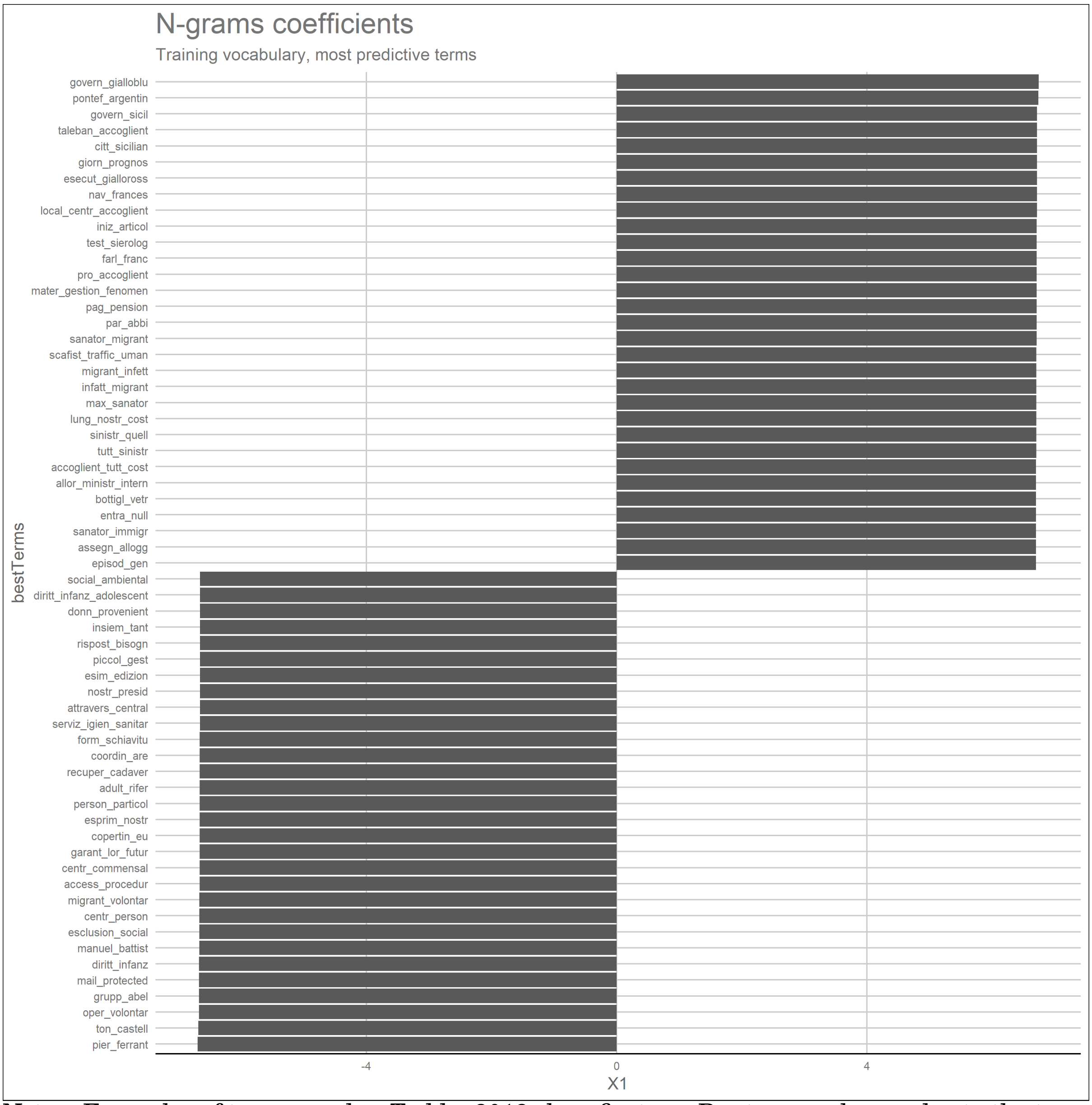
In Taddy, 2013's procedure, for each document i, equipped with term counts

$\mathbf{x}_i = [x_{1i}, ..., x_{Ji}]'$, the n-gram total counts for labels $y \in \{0, 1\}$ are defined as $x_y = \sum_{i:y_i=y} \mathbf{x}_i$. Given row sums $m_i = \sum_{j=1}^{J} m_{ij}$, the multinomial inverse regression would then be:

$$\mathbf{x}_y = MN(\mathbf{q}_y, m_y) \text{ with } q_{yj} = \frac{exp[\alpha_j + y\phi_j]}{\sum_{l=1}^{J} exp[\alpha_l + y\phi_l]}, j = \{1, ..., J\}, y \in \{0, 1\} \tag{2.13}$$

Where MN is a j-dimensional multinomial distribution with size $m_y = \sum_{i:y_i=y} m_i$ and probabilities $q_y = [x_{y1}, ..., x_{yJ}]'$. Under a set of conditions, a sufficient reduction score for frequency $\mathbf{f}_i = \mathbf{x}_i/m_i$ is defined as $\mathbf{z}_i = \boldsymbol{\phi}'\mathbf{f}_i, \implies y_i \perp\!\!\!\perp \mathbf{x}_i$. Given this score, the forward regression would simply be a univariate model, which in the present case, take logistic form: $E[Y] = \frac{1}{e^{\beta_0 + \beta_1 z_i}}$. The author proposes a so-called *gamma-lasso* algorithm to find a joint maximum a posteriori estimate of both coefficients and their prior scale, by maximizing the log-likelihood of the model with a lasso penalty, with λ_j possibly varying with j. Further details on this estimation are in the author's contribution. Although the two alternative models produced very similar labeling, a set of validation steps leads to the adoption of Taddy, 2013's measure as the baseline slant index. Figure E.3 represent some predictive terms, with associated scores. Terms with negative values in the x-axis predict slant negatively, while those with positive values are positive predictors of slant.

Figure E.3: Most predictive coefficients, Taddy 2013.



Notes: Examples of terms used in Taddy, 2013 classification. Positive x values indicate the term impacts the slant prediction positively. Vice versa, negative values in the x-axis mean the term is a negative predictor of the slant index.

Given this binary classification of documents, average indicators are computed at month-year level for each municipality. These aggregate averages then can be interpreted as a proportion of right-slanted news out of migrant-related news to which a particular municipality was exposed. Importantly, given the news geo-localization described in the previous section, a document (news piece) can be read in more municipalities. When constructing these averages, importance weights were used according to the Google Trends based information, as detailed in section 2.D.

Media Slant Validation and Exploration

This section explores the validation procedures undertaken for the construction of the anti-immigrant slant index.

To establish the prediction precision for the labelling process, a 10 fold cross-validation procedure was performed on both the baseline and the alternative anti-immigrant slant index. Table E.1 below presents cross-validation results.

As a further measure of validation, results were also compared with human classification of roughly 1000 entries. This sample was extracted randomly from the main corpus, with source-based stratification. The same text was analyzed by two individuals from the population of the platform *Amazon Mechanical Turk*. Having two respondents instead of one for the same task allowed for possible variation in the response. At the same time, this variation, though minimal, allows to partly account for subjective biases in the response. Interestingly, this procedure revealed some evidence that human classification of slant is likely heavily influenced by predetermined ideology: human classifiers did not agree on slant in 27 % of the instances. Below, the full instructions entered in the platform are provided.

ORIGINAL TEXT:

Instructions: Per favore, legga il testo qui sotto elencato. Le si chiederà di interpretare se il contenuto della news ha un'accezione politica. Recentemente, il dibattito politico in Italia si è incentrato molto sul tema della migrazione. In generale, i partiti a destra sostengono un'ideologia critica riguardo ai recenti sbarchi dei richiedenti asilo, e del loro arrivo in Italia, affermando per esempio problemi sicurezza emergono per i cittadini. Il centro sinistra si è visto più propenso all'accoglienza. Le viene domandato se l'articolo afferma, anche generalmente/indirettamente/secondariamente, il tema della migrazione. Per esempio se l'articolo riporta un furto ad opera di individui stranieri presenti in Italia, il tema della migrazione, per quanto indirettemente, è presente. Se l'articolo parla soltanto di eventi cultura o di turismo, in quel caso non affronta il tema della migrazione. Le sarà poi chiesto di valutare se da chi ha scritto l'articolo si evince un tono vicino ad un'ideologia politica (e quale). Per esempio: -se l'autore sceglie il termine "nullafacenti" per descrivere dei cittadini stranieri/ migranti, si evince un tono critico sulla migrazione, e quindi maggiore vicinanza al discorso di destra. -Se l'articolo giudica importante o necessario un evento di accoglienza organizzato nel Comune di riferimento, questo tono è piu' vicino al discorso di sinistra. Infine le viene domandato se il SOGGETTO dell'articolo, di cui il testo parla, ha un'inclinazione ideologica e quale. Per esempio, se il testo menziona la decisione di un sindaco di non approvare un progetto di accoglienza nel nome di una maggiore sicurezza dei cittadini, il soggetto dell'articolo si categorizza di un'ideologia più a destra. (NOTA:La vicinanza politica dell'autore puo' differire da quella del soggetto del testo). Un'ultima sezione le chiede un breve commento sulla sua scelta, basta la citazione di un punto del testo, una parola chiave o una sua breve frase che confermi che le risposte sono inserite a seguito di una sua valutazione.

Testo dell'articolo:[...]

Questo articolo parla, anche generalmente, di migrazione? Risponda con SI o NO.

I fatti descritti nell'articolo sono delineati neutralmente o con un'accezione ideologica? Risponda con N se neutralmente, e con O se pensa esista del contenuto ideologico.

Il tono di questo articolo ha una somiglianza con il discorso politico di destra/centro-destra, di sinistra/centro-sinistra o nessuno dei due? Risponda con una delle tre opzioni: DESTRA; SINISTRA o NEUTRO.

Questo articolo menziona l'opinione o i fatti di una persona (un politico o cittadino o un intervistato) di destra/centro-destra, di sinistra/centro-sinistra o nessuno dei due? Risponda con una delle tre opzioni: DESTRA; SINISTRA o NEUTRO.

Indichi una frase o parola del testo che motivi la sua scelta. Basta una breve risposta. Se l'articolo non parla di migrazione (risposta 1), puo' inserire NOMIG.

ENGLISH VERSION:

Instructions: Please read the text below.

You will be asked to interpret if the news content has a political meaning. Recently, the political debate in Italy has focused a lot on the issue of migration. In general, the parties on the right support a critical ideology regarding the recent landings of asylum seekers, and their arrival in Italy, stating for example security problems arise for citizens. The center left has seen more inclination to their reception. You are asked if the article affirms, even generally / indirectly / secondarily, the theme of migration. For example, if the article reports a theft by foreign individuals present in Italy, the theme of migration, albeit indirectly, is present. If the article speaks only of cultural or tourism events, in that case it does not address the issue of migration. You will then be asked to evaluate if the writer of the article reveals a tone close to a political ideology (and which one). For example: -if the author chooses the term "deadbeat" to describe foreign citizens / migrants, there is a critical tone on migration, and therefore greater proximity to the right-wing discourse. -If the article judges a welcome event organized in the relevant Municipality to be important or necessary, this tone is closer to the left-wing discourse.

Finally, you'll be asked if the SUBJECT of the article, of which the text speaks, has an ideological inclination and which one. For example, if the text mentioned a mayor's decision not to approve a reception project in the name of greater citizen safety, the subject of the article categorizes with a more right-wing ideology. (NOTE: The political closeness of the author may differ from that of the subject of the text).

A last section asks you for a brief comment on your choice, you just need to quote a point in the text, a keyword or a short sentence from it to confirm that the answers are inserted after your evaluation.

Article text:[...]

Does this article also talk about migration, even generally? Answer with YES or NO.

Are the facts described in the article outlined neutrally or with an ideological meaning? Answer with N if neutral, and with O if you think there is an ideological content.

Does the tone of this article bear a resemblance to right / center-right, left / center-left political discourse, or neither? Answer with one of the three options: RIGHT; LEFT or NEUTRAL.

Does this article mention the opinion or facts of a person (a politician or citizen or an interviewee) on the right / center-right, left / center-left or both? Answer with one of the three options: RIGHT; LEFT or NEUTRAL.

Indicate a sentence or word of the text that motivates your choice. A short answer is enough. If the article does not talk about migration (answer 1), you can enter NOMIG.

The questionnaire allowed for a different answer for two potentially different cases. In case one the news author writing contains some ideological inclination; in case two the subject of the article involves a person's opinion (or facts) that contains a political tendency. For the scope of this study a broad definition of media bias is adopted in constructing the measures. No distinction between the two cases is investigated, and giving voice to third persons with a political orientation is considered on the same level of writing with that orientation (recall, as broadly similar approaches, Groseclose and Milyo, 2005 who define media-slant based on think-tank citations; Gentzkow and Shapiro, 2006 estimating informative words via a data-driven approach, Taddy, 2013's refinement; Flaxman et al., 2016 who propose a non text-based measure, based on the geographic distribution of readership and voters rather than on text; Djourelova, 2020 who focuses on the banned use of the expression "illegal immigrant").

Comparisons of the slant indices with human classification is displayed in Table E.1.

Generally, the two measures appear to be fairly comparable: the accuracy for Taddy's measure (i.e., the proportion of correct classifications over the total sample size) is estimated to be 0.786 with a standard deviation of 0.0016. The elastic-net measure has estimated accuracy of 0.777 with a standard deviation of 0.006, suggesting a slightly lower precision estimate though accompanied by slightly more stability (smaller variability). When compared to the human classification, accuracy is not a good performance indicator, as labels are unbalanced for the 1000 entries: the majority are labeled as 0.[87] Therefore, the Younden-J metric (1-specificity -sensitivity) is reported, alongside a sensitivity and specificity. Sensitivity corresponds to the share of 1-labeled instances, over the 'true' 1 valued entries. Specificity refers to the share of 0-assigned observations, over the total of true zeros. All in all, these statistics appear to favor the use of Taddy, 2013's index over the Elastic-net, as a benchmark indicator. They also point to a better performance in terms of correctly identifying the lack of slant, rather than its presence. This may suggest that the media-slant outcomes may suffer from an attenuation bias and can therefore be conceived as a lower bound.

Table E.1: Cross-validation results

	Cross validated		*Out of sample*			*Human classification*		
Model	*Mean accuracy*	*St. dev.*	*Accuracy*	*Specificity*	*Sensitivity*	*Younden-J*	*Specificity*	*Sensitivity*
Taddy, 2013	0.786	0.016	0.739	0.646	0.826	0.239	0.761	0.472
Elastic Net	0.777	0.006	0.733	0.652	0.826	0.214	0.758	0.456

Notes: Performance results from the two generative models. Performance in the left section is based upon a 10-fold cross validation, done manually for Taddy, 2013. Package *cv.glmnet* performs cross validation automatically. In the middle, an out of sample prediction is based on a test-set left aside from the training sample. The right-most columns include comparisons with human classification of 1000 entries.

2.F Municipalities in Sample

Table F.1: List of municipalities in the baseline panel

Municipalities:	Airole; Alassio; Albenga; Albisola; Albissola; Altare; Andora; Apricale; Aquila D'arroscia; Armo; Arnasco; Aurigo
.	Badalucco; Bajardo; Balestrino; Bardineto; Bergeggi
	Boissano; Bordighera; Borghetto D'arroscia; Borghetto Santo Spirito; Borgio Verezzi; Borgomaro; Bormida
	Cairo Montenotte; Calice Ligure; Calizzano; Camporosso; Caravonica; Carcare; Carpasio
	Casanova Lerrone; Castel Vittorio; Castelbianco; Castellaro; Castelvecchio Di Rocca Barbena
	Celle Ligure; Cengio; Ceriale; Ceriana; Cervo; Cesio
	Chiusanico; Chiusavecchia; Cipressa; Cisano Sul Neva; Civezza; Cosio D'arroscia; Cosseria; Costarainera
	Dego; Diano Arentino; Diano Castello; Diano Marina; Diano San Pietro; Dolceacqua; Dolcedo; Erli; Finale Ligure
	Garlenda; Giustenice; Giusvalla; Imperia; Isolabona; Laigueglia; Loano; Lucinasco
	Magliolo; Mallare; Mendatica; Millesimo; Mioglia; Molini Di Triora; Montalto Ligure; Montegrosso Pian Latte; Murialdo; Nasino; Noli
	Olivetta San Michele; Onzo; Orco Feglino; Ortovero; Osiglia; Ospedaletti
	Pallare; Perinaldo; Piana Crixia; Pietra Ligure; Pietrabruna; Pieve Di Teco; Pigna; Plodio
	Pompeiana; Pontedassio; Pontinvrea; Pornassio; Prelà; Ranzo; Rezzo; Rialto; Riva Ligure; Roccavignale; Rocchetta Nervina
	San Bartolomeo Al Mare; San Biagio Della Cima; San Lorenzo Al Mare; Sanremo; Santo Stefano Al Mare; Sassello; Savona
	Seborga; Soldano; Spotorno; Stella; Stellanello
	Taggia; Terzorio; Testico; Toirano; Tovo San Giacomo; Triora; Vado Ligure; Vallebona; Vallecrosia; Varazze; Vasia
	Vendone; Ventimiglia; Vessalico; Vezzi Portio; Villa Faraldi; Villanova D'albenga; Zuccarello

Notes: Final list of Municipalities in the panel, resulting from the news geo-localization.

[87] human classification returned 73% of 0s; Taddy, 2013's measure returned 68% and the elastic-net model returned 67%

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Chapter 3

The International Drivers of Asylum Policy

Abstract

In this paper, we explore the role of international interactions in affecting asylum policies: i.e. how a country's policy implies a reaction of connected countries. We complement the existing empirical literature by adopting a flexible Spatial Dynamic Panel Data model that allows us include both time and space autocorrelation in the policy measures, as well as space dependencies in the explanatory variables. Importantly, we separate out strong cross-sectional dependence stemming from heterogeneous responses to unobserved common shocks. This step proves crucial for the identification of spatial effects. We exploit data on acceptance rates and a measure of speed in processing requests, for 23 European countries at quarterly frequency between 2013 and 2019. By relying on numerical observables, we avoid the issues of quantifying qualitative policy measures. Additionally, we allow spatial interactions across countries to take place along the geographic dimension, but also along linguistic proximity. Results show asylum policies are strategic substitutes, with key results featuring for both dimensions of interactions. Finally, we document spillover effects emerging from Germany's reception announcement in September 2015 on cross-country processing speed, as well as significant indirect effects resulting from the arrivals of migrants at the external EU borders.

3.1 Introduction

According to the latest UNHCR's Refugee Population Statistics, about 630 890 people applied for asylum in the European Union (EU) in 2021. Asylum applications in the EU reached a peak in 2015 and 2016 and dropped thereafter, featuring a a 33.5% increase between 2020 and 2021, largely favoured by the establishment of the new Taliban regime in Afghanistan.[88] More recently, figures of asylum seekers have been raised by the war in Ukraine.[89] The pressure exerted on the asylum systems of EU countries by the Ukrainian diaspora has revived the debate over a common asylum framework across the EU. Yet the issue is long standing.

Key factors as the Union founding right of 'freedom of movement' and the sharing of external borders exposed to the Mediterranean, the African and the Balkan routes have incentivised attempts to coordinate migration and asylum policies in the last three decades. Decisive steps in the development of a European asylum policy date back to the starting point of the Common European Asylum System (CEAS) reform, in 1999. The CEAS has established the basic mechanisms for determining the Member State responsible for examining asylum applications (replacing the intergovernmental 1990 Dublin Convention). In 2009 the Lisbon Treaty entered into force, moving from the CEAS definition of minimum criteria towards the setting of a common asylum system, comprising a uniform status and procedures. Whereas EU countries have formally agreed on the harmonisation of migration and asylum policies through the subscription of the Treaty, this has not yet translated into the actual implementation of homogeneous policies at EU level. Lastly, on 23 September 2020, the European Commission issued the New Pact on Migration and Asylum, in an attempt to give a fresh start to the stalled CEAS reform.

As of today, asylum seekers are not treated uniformly across the EU.[90] The proportion of positive asylum decisions varies greatly across countries and asylum application processes are still far from being standardized. As a result, asylum seekers travel around Europe and apply for asylum in the countries where they believe they will have a higher chance of receiving international protection.

In absence of commonly applied standard procedures in the asylum application and approval process, the decisions taken at one country level can reverberate into the asylum policies applied by other countries. Giordani and Ruta, 2013 outlines four main drivers of immigration policy: i. distributional determinants, including the effect of immigration on the labor market and on welfare systems (Borjas, 1994); ii. political economy factors, whose relevance depends on institutions and voting and/or lobbying activity by interest groups standing to lose or gain from

[88] Figures for 2020 and 2021 do not include applications made in the UK (following its withdrawal from the EU).

[89] Ukrainian citizens can also apply for "temporary protection" and do not have to necessary undergo the asylum application process.

[90] For a discussion see *Asylum Report 2022*, European Union Agency for Asylum (EUAA), 2022.

immigration (Facchini et al., 2006); iii. non-economic (cultural) forces, such as racism or xenophobia, also play a role (Dustmann & Preston, 2007); iv. the policy decisions of other countries.[91]

Descriptive evidence from Boeri and Brücker, 2005 suggests that the asylum policies implemented by a single European country can indeed concur in the definition of the policies in other countries. Notably, on September 4 2015 Chancellor Angela Merkel pronounced the famous "we can do this" ["*wir schaffen das*"] speech, through which Berlin has unilaterally decided to welcome thousands of migrants from the outbursting Syrian refugees' crisis and more. The decision, allegedly taken without consulting the European institutions and remaining member states (Engelen, 2015), has translated into varying reactions across the EU, including anti-refugees advertisement campaigns promoted by the Hungarian and the Danish governments[92]. However, the direction and the extent of potential cross-country diffusion effects of asylum policies turn to be empirical questions. To this regard, the EU in the years 2000s represents an ideal setting of investigation, both because of the variations occurred in asylum applications across the Union and given the heterogeneous responses taken at country level to the so-called 'migration crisis'.

Understanding the transmission mechanism/s through which more or less restrictive asylum policies may spread across Europe is of key importance in supporting the development and actual implementation of an harmonized asylum policy framework.

In this paper, we investigate the role of cross-country interdependencies in explaining policy decisions on asylum reception. To do so, we employ a spatial specification that allows potential interactions to be modelled on the basis of geographic proximity, but also along the dimension of cultural-linguistic proximity. The presence of spatial correlation would signal that despite an overall common agreement, member states tend to cluster their policy decisions based on the decisions of closely connected countries. With the help of a spatial dynamic panel model with interactive fixed effects, we separate the (possibly heterogeneous) effects of unknown common factors, that lead to a strong cross-sectional dependence in the data. Strong cross-sectional dependence may interfere in the estimation of spatial effects, while the direction of this confounding is not *a priori* unambiguous.

In addition to factoring-out strong cross-sectional dependence, we adopt a dynamic spatial specification that controls for the effect of time, as well as simultaneity issues arising from our outcome variables being both at the left and right-hand side of our estimation equation. To do so, we adopt Shi and Lee, 2017's estimator, which is a novel approach in the literature on the drivers of migration policy.[93]

We focus on measurable policy outcomes, namely acceptance rate and processing

[91] Giordani and Ruta, 2013 develop a theory in which unilateral, strategic decisions of countries with respect to immigration policy provoke leakage effects and result in inefficiencies.

[92] https://www.bbc.com/news/world-europe-34173542,
https://www.hrw.org/news/2016/09/13/hungarys-xenophobic-anti-migrant-campaign

[93] Unlike in Shi and Lee, 2017, we do not include a measure of α in our estimation.

speed, in a similar vein to Bertoli et al., 2022. As discussed in Section 3.4.1, this represents a first addendum to the existing literature on the role of cross-country interactions on migration and asylum policy, currently proposing a variety of qualitative outcomes, which hinders interpretation and comparability across findings. Our framework proves convenient to estimate dynamic spillover effects of explanatory variables of interest. We focus on two in particular, i.e. i) the positive reception announcement introduced by Germany in 2015: we measure the diffusion effect, if any, exerted on the asylum policy-making of other EU countries; ii) the effects of migrants arrivals at the main external gateway countries in Europe, following the migratory routes defined by the European Border and Coast Guard Agency (henceforth FRONTEX).

Finally, a contribution of this paper involves the study of how different dimensions of proximity matter in the diffusion effects, whether this could be either spatial or linguistic.[94]

Our results show that considering strong cross-sectional dependence is key when exploring the role of spatial interactions. Spatial relations differ substantially in size and significance, once we have controlled for the heterogenous effects of common unknown factors. We find that omitting interactive effects overestimates the spatial interdependence parameters in both acceptance rates and processing speed. Once we account for interactive effects, we find countries to be strategic substitutes in acceptance rates. This is partially in line with Görlach and Motz, 2021's model who also describes such relations across some European countries (though without a regression framework). Drawing a parallel with their arguments, when a country becomes more accepting, a tightening response of other countries could rise if these countries fear leaking inflows, caused by a greater attraction of migrants towards the direction of the accepting country. Similarly, when a country exogenously decreases its processing speed, neighbors react by treating applications more rapidly, especially for origins for which a positive outcome is less likely to result. The higher the speed in one country, the lower the burden of an elongated hosting period, especially if migrants will then be repatriated due to unfunded claims. Crucially, these results are robust to the choice of the dimension - i.e. geographic or linguistic - for interaction matrices.

Additionally, we observe that the arrival of migrants at the external EU borders decreases the acceptance rates in geographic neighbors, and increases their speed of processing applications. We see this as evidence that pressure at the borders leads to an indirect reaction of countries to minimize the costs of an elongated reception stage. Despite these considerations, we find that the declaration of Germany to open their doors to asylum requesters in September 2015 led to a relaxation of processing speeds of connected countries. This possibly indicates that with Germany taking a

[94] See for instance the work of Case et al., 1993; Conley, 1999 for examples of the salience of non-geographic types of economically meaningful distance. See also Manski, 1993 to see how interactions can be also understood as an endogenous social behaviour.

leading role, other countries respond by relaxing their processing efforts.

We proceed as follows. In Section 3.2 we present the advantages of SDPD models to this literature. Relevant reference literature is reviewed in Section 3.3. We present data sources and policy measurement challenges in Section 3.4. Our results are outlined in Section 3.5 and we provide conclusive remarks in Section 3.6.

3.2 Modelling policy spillovers

A country's policy choice is not only driven by its own characteristics, as social fabric, historical background and political setting - but it rather follows from its characteristics in relation with related countries own features and policy decisions. Hence a response to both internal and external factors. Spatial models typically address how such underlying interrelations give rise to cross-country spillover effects, by modelling these interactions explicitly along the dimensions that locally relates one another the unit of investigations.

Yet, at the same time, individual countries can react differently to common unobserved shocks (Bai, 2009; Pesaran, 2006). The presence of such unobserved common factors may result in the spurious co-movements in policy adoption across countries, whether these may be meaningfully connected or not. Cross-sectional correlations emerging from common factors are a form of strong or *global* cross-sectional dependence (see the seminal work of Pesaran, 2006), while spatial interactions refer to the framework of weak or *local* cross-sectional dependence (see for instance the pioneering contribution of Cliff and Ord, 1973).

Ultimately, our goal is that of providing a reliable estimate of the local interdependencies in the decisions of countries around asylum reception. In particular, we allow for spillovers to occur not only geographically, but also on the grounds of linguistic proximity. This twofold approach translates into investigating potential responses in country j to asylum policy changes in country i that travel either across geographic or cultural distance. In fact, borrowing from the literature in cultural economics, we proxy cultural distance with linguistic distance, as it has been commonly done across social and political science studies over the last two decades.[95]

3.2.1 Identification

In our argument for the spatial specification, countries are more sensitive to the decisions of other countries, if the changes in these other countries have likely consequences spreading to their own situation. As in the context of Agersnap et al., 2020 and Bratu et al., 2020, Denmark decisions on migrant receptions appear to be

[95] See Alesina et al., 2003 and Fearon, 2003 for a seminal discussion and Ginsburgh and Weber, 2014 as comprehensive reference for the use of linguistic distance as a proxy of culture.

related to migrants reaching other Nordic countries. Within the context of the migration crisis of the 2010s, the migratory routes of asylum seekers and undocumented migrants led to several tensions in various country borders (for example, several NGO reports signal the presence of migrants in precarious conditions attempting to cross the borders between Italy and France, between Spain and France, between France and the UK).[96] Given these tensions, neighboring countries are reasonably aware and possibly reactive to the flows of migrants in their most direct geographic substitutes.[97]

With our empirical strategy, we test the null hypothesis that the spatial arrangement of policy decisions is random. The alternative is that the spatial arrangement follows geographic (and/or linguistic) proximity, which we motivate as signaling a cross-neighbor reaction in asylum receptions. To claim that spatial autocorrelation follows from cross-country reactions in asylum responses, we face at least 2 challenges. First, we need to address the presence of possible unobserved factors that may drive policy decisions into similar directions. Secondly, we have to account for a simultaneity bias that results from introducing spatial lags of the dependent variable in the right hand side. We address these two issues by means of a spatial dynamic panel data model with interactive fixed effects, as proposed by Shi and Lee, 2017. This specification estimates heterogenous responses to unobserved common factors as interactive effects à la Bai, 2009, which are allowed to potentially correlate with the included regressors. Spatial interactions and interactive effects are modeled jointly, and the spatial components have a flexible, dynamic form.

While interactive effects absorb heterogeneous impacts from common shocks on cross-section units, idiosyncratic variables may also confound the degree of local interdependence, if they exhibit spatial correlation and vary with time. We note that we are concerned with these unobserved factors, if they are time-varying, because the individual fixed effects absorb the time invariant unobservables. As an example of the concern we may face, a set of countries may apply similar asylum responses because they receive a similar amount of asylum applications, and not because they imitate or counteract the decisions of one another. To address this concern, we also augment the model with a rich set of covariates, which enter the model together with their spatial lags. For instance, we control for both the number of applications in country i and for the number of applications in the connected countries j. We control for the presence of a populist party in country i and in the neighborhood. We also control for demographic and economic aspects, as well as a proxy for the level of welfare. The full set of covariates will be detailed in the data description of Section 3.4. We acknowledge that there could still be a set of unobserved factors that is not taken care of in our approach. Further we are aware that some of our

[96] See, for instance, http://www.infomigrants.net as a collection of information on these cross-border tensions.

[97] We also allow for linguistic substitutes to capture a proximity of institutions and cultures that are not fully correlated with the geographic dimension, but that could still saliently represent the degree of sensitivity and exposure to information across countries.

covariates might be endogenous, leading to the point-estimates on their marginal effects to be potentially inconsistent. For this reason, we prefer focusing on the interpretation of indirect effects of covariates that less likely suffer endogeneity concerns, such are the arrivals of migrants at the external EU borders. We believe we address several reasonable concerns but do not claim our main findings are fully interpretable as causal. Still, to the best of our knowledge, our contribution is the first to address several points previously discarded in the economics literature looking and migration policy interactions.

Finally, simultaneity bias concerns are explicitly addressed in the QML specification.[98] Crucially, the chosen functional form allows for flexible time dynamics. This is key to avoid estimating spurious spatial effects (Fischer, 2021).

Our spatial dynamic panel data (SPDP) specification is as follows:

$$y_{it} = \rho y_{it-1} + \lambda_1 W y_{it} + \lambda_2 W y_{it-1} + X_{it}\beta_1 + W X_{it}\phi_1 + \Gamma_i f_t + u_{it} \tag{3.1}$$

Where: y_{it} is the policy outcome of interest for country i at time t; W is an interaction matrix based on one of the two dimensions alternatively considered (geographical, cultural-linguistic). $y_{it-1}, W y_{it}$ and $W y_{it-1}$ are respectively the time lag, a contemporaneous space lag, and a time-space lag of outcome$y$. Individual countries are allowed to be impacted by time varying unknown common factors f_t. Such factors can have heterogeneous effects on the cross-sectional units, as captured by the factor loading parameter Γ_i. The number of unobserved factors in vector f_t is assumed to be a constant $r << n, T$. Their inclusion allows to flexibly assess how spatial interactions take place: simultaneously and/or in the next period, and how persistent is their impact. Parameters ρ, λ_1 and λ_2 jointly capture these time-space dynamics. Our set of covariates is included in vector X_{it} and its spatial lag WX_{it}, while u_{it} is an i.i.d. idiosyncratic shock.

Relatively to the existing literature that models migration policy interdependence, to the best of our knowledge, we are the first to empirically address the confounding role of strong cross-sectional dependence, and to combine both time and space autocorrelation in the policy measures with space dependencies differing for each explanatory variable, as captured by the contextual characteristics term WX_{it}. We also add to the literature by adopting a consistent estimator that accounts for the simultaneity of interactions in country policies. Importantly, we exploit data on acceptance rates and estimated processing speed for 23 European countries at quarterly frequency between 2012 and 2018 (T=28).[99] By relying on numerical observables, we avoid the issues of quantifying qualitative policy measures.

[98] Such bias prevents the use of OLS or within estimators.

[99] Shi and Lee, 2017's estimator requires both a large N and a large T. Their Monte-Carlo simulations are reported starting with N=25, T=25, reporting an acceptable performance, which however improves in larger samples.

3.3 Literature

The *Common European Asylum System* (CEAS) was launched in the late nineties with the goal of establishing a cooperation framework at EU level, based on the principles of the 1951 Geneva Convention. Yet, the goal of a common European asylum policy is far from reaching reality in the current scenario (Dustmann et al., 2017; Fernández-Huertas Moraga & Rapoport, 2015; Hatton, 2015).

The recent literature provides some examples of the 'race to the bottom' in the immigration policy openness of individual countries. The example of Denmark is recurring in the literature. The country reintroduced a welfare cut to non-EU migrants in 2015. Agersnap et al., 2020 find evidence that this cut succefully reduced inflows of migrants relative to other Nordic countries. Bratu et al., 2020 document that the imposition of stricter rules on family reunification in Denmark in 2002 resulted into outflows of second-generation migrants to Sweden.

More broadly, Brekke et al., 2017 cover 9 Western Europe destinations and find evidence that policy restrictions divert migrants flows to other destinations. In their bilateral setting, the authors point at the importance of capturing patterns of multilateral resistance to migration. Bertoli and Moraga, 2013 introduced this term for gravity-like analysis of migration flows data, borrowing from the trade literature. Migration between origin o and destination d doesn't only depend on the characteristics of the country pair, but also on the variables related to other destination countries. Giordani and Ruta, 2013 term migrants deflections externalities a leakage effect. They introduce a model that explains how this leakage leads to strategic immigration policy and inefficient coordination failures, from the welfare perspective.

As pointed out in Hatton, 2014 and Rayp et al., 2017, the exploration of the drivers of immigration policy has been more prevalent in the political science field, and scarcer in the economics domain. This occurred despite a strong and overlapping policy interest of this research question, common to both disciplines. Focusing on the drivers of immigration policy in Europe, Boeri and Brücker, 2005 study the Eastern enlargement of EU and introduce a theoretical framework describing the "race to the top" in immigration barriers. Their findings highlight the key roles of natives preferences, inflows diversion, and policies spillovers. The authors also provide descriptive evidence of positive cross-country correlation in policy strictness, leaving space for future empirical research to explore this interrelation evidence more formally. Görlach and Motz, 2021 focus on refugee migration and propose a model of refugees' location choices and strategic interaction among neighbor destinations in a dynamic setting. Their calibrations on the Syrian inflows to Europe show that recognition rates are strategic susbsitutes in the south and southeastern Europe, and strategic complements in northern Europe.

While the literature is richer in identifying how stricter policies provoke sorting and deflection of migrant flows, studies investigating the drivers of immigration policies are more scares. Volden et al., 2008 highlight that the key issue in applied studies investigating policy diffusion is to empirically discern cross-learning from myopic policy adoptions.

Hatton, 2004 is among the contributions that provide an empirical assessement and focus on asylum flows and policy in 14 EU countries, in the 1980s and 1990s. The author adopts an index of asylum policy constituted by a set of dummies describing major changes in the policy stance. A *space-time recursive* model brings evidence of a strong time persistence, and a significant positive spillover effect of neighbors policies. The author further documents that asylum applications in other countries toughen the country's policy. Differently from the author's approach, we enlarge the set of covariates and allow for individual and time fixed effects in the model. Importantly, time fixed effects may capture the fact that countries exposed to common shocks react in a similar fashion, though *independently*, without a real interaction dimension. This argument is raised in Volden et al., 2008 who warns applied scholars interested in investigating policy diffusion.

Brücker and Schröder, 2011's model predicts that neighboring countries follow each other in implementing selective immigration policies. They test this prediction empirically with a panel of 15 OECD countries, spanning 1980-2005. The data source for migration policy originates from Ortega and Peri, 2013 and cross-country dependency is considered along a geographic, a linguistic and an income dimension. Their space-time recursive specification suggests a positive spillover. This result, however, is rather descriptive: the authors only control for own country's gdp per capita and their dynamic specifications omit time fixed-effects.

Rayp et al., 2017 point out the difficulty in quantifying migration regulations. This challenge slowed down the interest of scholars in addressing the drivers of immigration policy. As there's a substantial degree of arbitrariness in assigning numerical values to the size and direction of policies, estimates resulting from a singular approach may be unreliable. Rayp et al., 2017 circumvent this problem by aggregating an index from several sources through a Bayesian state-space model specification. Past policy values are used to predict the present policy, and to impute on missing values. Differently from our approach, the authors adopt a static spatial model to estimate cross-country relations in migration policy, disregard policies targeting asylum migration, and do not consider spatially lagged regressors as potential covariates in their model: e.g. they do not consider the role of migration of country j on the policy restrictiveness of country i.

As a final remark, it is worth mentioning a more indirectly connected literature on the public economics of tax competition (Brueckner, 2003; Case et al., 1993; Moriconi et al., 2019). In this literature, countries strategic policy choices on taxation levels are modelled as best responses to (an average of) the decisions of connected countries.

More broadly, the idea that policy makers in different states or countries may learn from one another has long been of interest among the political science scholars, implying a substantial literature in this area (see Gilardi, 2010; Graham et al., 2013). Thinking of the EU scenario, a clear parallel can be made between the strategic decision making process of governments across public policies adoption, and decisions involving the reception of migrants.

3.4 Data and measurement

3.4.1 Policy outcomes

Measuring immigration policy is a delicate task that has provided some measurement challenges across the reference literature (De Haas et al., 2015; Hatton, 2014; Rayp et al., 2017). Our focus on asylum policy is motivated by two aspects. The first aspect is that immigration policy is not homogenous towards all target groups. For example, they may be skill (Burzynski, 2018), or origins-based.[100] Analyzing overall immigration policies without taking into account these heterogenous groups may lead to partial, incomplete findings. Another reason to focus on asylum migration is that this type of undocumented migration has characterized the international debate in the recent decades in Europe, within the context of the so-called migration crisis. In this context it has emerged that there was an absence of an up-to-date joint scheme within Europe to effectively handle the unprecedented inflows of migrants (Bertoli et al., 2022), which possibly led to non-cooperative behavior of national governments.

We adopt Bertoli et al., 2022's approach to measure numerically policy restrictiveness in the context of the recent asylum migration to Europe and rely on Eurostat for the following country-level statistics: monthly data on persons subject of asylum applications pending at the end of the month; quarterly data on first instance decisions on applications.

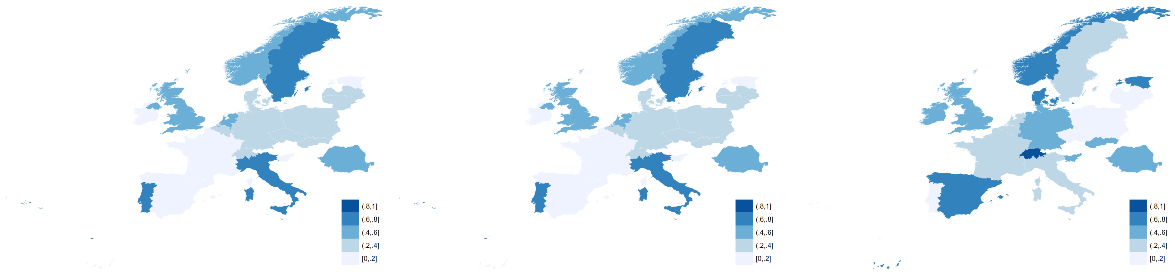
We focus on 2 outcomes that we can retrieve at quarterly frequency:
Acceptance rates: Percentage of first-instance decisions with a positive outcome -i.e. decisions granting refugee/subsidiary protection status, authorisation to stay for humanitarian reasons and temporary protection. We find an average acceptance rate in the sample of $\sim 46\%$, with a standard deviation of 22%. In Figure 3.4.1, we report how acceptance rates spatially distribute for three time periods. From left to right respectively, we present figures for the first quarter of 2013, for the 3rd quarter of 2015 and for the last quarter of 2019. Darker shades represent higher values. We see acceptance rates tend to distribute unevenly in the sample of interest. Italy, Portugal and Sweden having higher figures in the first 2 periods, while some changes over time also appear, especially between 2015 and 2019. For instance, acceptance rates seem to have increased in Portugal, Switzerland and Estonia, and

[100] An example is the free mobility for EU migrants within EU countries, or cases like Spain and the citizenship regulations which are more flexible for migrants from former colonies.

relatively decreased in some Eastern countries.

Figure 3.4.1: Acceptance rates, geographic distribution over time

(a) Q1, 2013 **(b)** Q3, 2015 **(c)** Q4, 2019



Notes: This figure reports the spatial distribution of acceptance rates and its evolution over time, for countries in the estimation sample. We show from left to right, respectively, acceptance rates for the first quarter of 2013, for quarter 3 of 2015 and for quarter 4 of 2019. Darker shades indicate a higher acceptance rate.

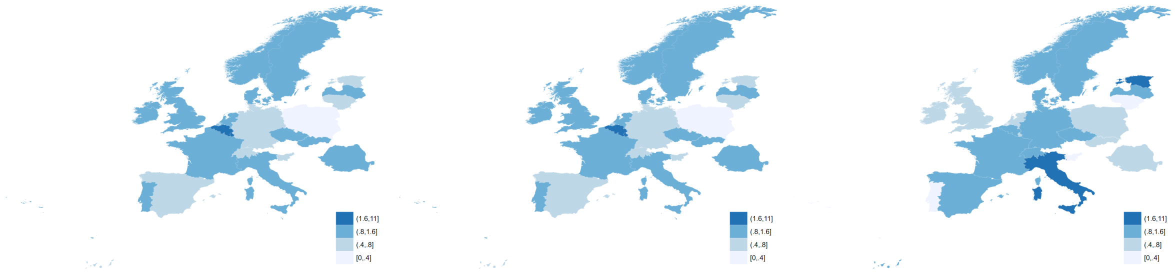
Processing speed: We proxy the speed of applications processing as the ratio of total decisions over the total of first instance asylum applications in the quarter. Bertoli et al., 2022 propose a estimate of processing speed that is based on the comparison of the cumulative sum of total applications over time, with the sum over time of pending applications.

Because this measure is by construction a function of the cumulative lags of applications, we opt for a simpler and more direct measure for processing speed that involves time t responses, which are the counts of undertaken decisions, which we rescale by the number of overall first-time applications so that we can compare different speeds with the number of applications taken as given.

In Figure 3.4.2, as shown for acceptance rates, we report how processing speed spatially distributes across time, comparing figures from the first quarter of 2013, from the 3rd quarter of 2015 and from the last quarter of 2019 (with darker shades representing higher values). We see some cross-sectional differences as well as differences over time for processing speed. While Belgium and Luxembourg appear on the top-side of the distribution for the earliest periods, We see countries such as Italy, Spain and Germany increasing their speed in the latest period. Countries as Romania and the UK appear on the opposite tendency: their speed seems decreases in the latest time periods, as opposed as the earliest years. We provide more details on the measures in Table 3.B.2.

Figure 3.4.2: Processing speed, geographic distribution over time

(a) Q1, 2013 **(b)** Q3, 2015 **(c)** Q4, 2019



Notes: This figure reports the spatial distribution of the speed of processing asylum applications and its evolution over time, for countries in the estimation sample. We show from left to right, respectively, processing speed the first quarter of 2013, for quarter 3 of 2015 and for quarter 4 of 2019. Darker shades indicate a higher speed. i/e/ a higher count of decisions given the total first-instance asylum applications.

Finally, we check how our main measures correlate with alternative, broader indices of migrant policy restrictiveness. To do so, we make use data from the Migrant Integration Policy Index (MIPEX, Solano & Huddleston, 2020). Mipex policy indicators evaluate countries along several items corresponding to three pillars: i) basic rights, ii) equal opportunities, iii) secure future. The resulting measure is a comprehensive score capturing the general degree of integration performance of countries. In table 3.4.1, we show results from a two-way fixed effects estimation of MIPEX values on each of the three asylum policy outcomes considered here. For each index, we present unconditional correlation coefficients, as well as coefficients conditional on the log count of asylum applications. We observe that countries engaging in higher acceptance of asylum seekers also perform more positively in terms of migrants' integration. Conversely, countries with higher speed of processing tend to score less positively in terms of migrants integration. As a suggestive channel, more politically or culturally hostile countries may have higher incentives to rapidly process asylum applicants. The same views howver reverse the incentives when it comes to giving (potentially costly) integration opportunities to migrants.

Table 3.4.1: Asylum policy outcomes and MIPEX

	Dependent variable: Mipex index			
	(1)	(2)	(3)	(4)
Acceptance rates	0.051**	0.052**		
	(0.015)	(0.016)		
Processing speed			-0.068***	-0.059***
			(0.017)	(0.017)
Observations	184	184	184	184
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Log. Applications		Yes		Yes

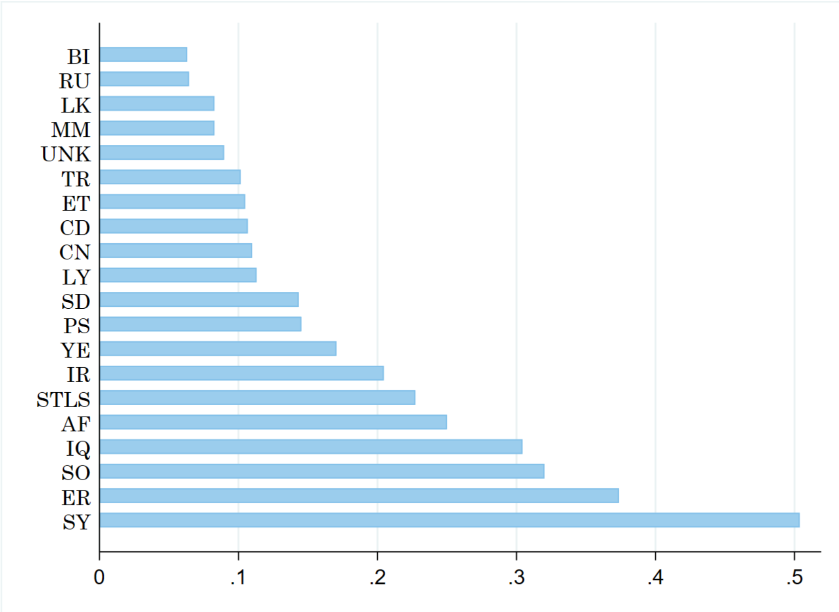
Notes: Correlation coefficients between policy outcomes and MIPEX, from a two-way fixed effect specification. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

As an extended result, we consider *Estimated processing times* as adopted in Bertoli et al., 2022. Given $a_{k(t-r;t)}$ = count of first-time asylum applications in receiving country k between month t-r-1 and month t-1 and given the stock of pending applications s_{kt-1} at the end of month t-1, the expected processing time equals the value of r s.t. $a_{k(t-r;t)} > s_{kt-1}$, and $a_{k(t-r-1;t)} < s_{kt-1}$. We find processing times to be centered around an average of 9.793 months, with a standard deviation of 6.974. This figures are unsurprisingly similar to those reported in Bertoli et al., 2022.

High-recognition origins

To extend our analysis, we also propose a set of estimates that specifically look at countries origins for asylum seekers who displayed a wider recognition rate. Specifically, we compute our outcome measures, by selecting applications and decisions for a specific destination and quarter, from origins that received a positive reception response in at least 60 percent of the cases. We summarize the data on the main high recognition origins in Figure 3.4.3, which shows that the most widely accepted origins in the data are Syria, Eritrea, Somalia, and Iraq. We include this extension, to better compare our results with the findings of Guichard, 2020 and Bertoli et al., 2022 who develop similar considerations in a gravity model framework. Guichard, 2020 explores migration outcomes related to asylum restrictions adopted by 19 OECD countries. The author focuses on a *safe country list* policy, which was adopted by 9 of these asylum recipients. For applicants coming from countries defined as safe, the asylum claim would be more easily flagged as unfounded, rejection would be most likely and the application procedure often accelerated. In a similar vein, we look at whether results differ along the distribution of the perceived legitimacy or asylum claims.

Figure 3.4.3: High-recognition origins



Note: Graph of the origin countries with highest acceptance in our data. Values correspond to count of entries in the destination, quarter-year data, for which the origin was accepted in at least 60 % of cases. Country codes follow the ISO 3166 code-list (3166-1 alpha-2), STLS corresponds to Stateless requesters and UNK stands for unknown origins.

3.4.2 Drivers of immigration policy

Following the literature (Giordani & Ruta, 2013; Rayp et al., 2017), our model covariates account for potential drivers of immigration policy. Economic and distributional determinants are: gdp per capita, unemployment, the degree of redistribution and welfare, measured by social protection benefits expenditures. These variables account for the fact that arriving migrants may compete with natives for welfare resources, which are more in demand where unemployment levels are higher, while gdp per capita accounts for the capacity of a country to receive migrants inflows. Demographic covariates, also linked to capacity and welfare demand, are population, stocks of immigrants, and inflows of asylum seekers, measured by the total asylum applications in the destination country and the counts in the presence of displaced people as reported by UNHCR. Non-economic, ideological factors are also important determinants of the political landscape, and therefore of the openness of migration regulations. We therefore control for the incumbency of a populist government in our regressions. Details on the sources and measurement of these covariates are discussed in Table 3.B.2.

3.4.3 Interaction matrices

We investigate whether country i's decisions influence (and are influenced by) the decisions of related countries $j \in J$. For our panel of 23 countries, listed in Table 3.4.2, we allow for alternative types of relatedness in asylum policy decisions, we propose interaction matrices based on two dimensions.

Geographic proximity: First, we consider the geographic dimension. Countries that are geographic neighbors are the immediate substitutes for migrants in precarious situations, whose journeys involved attempted border crossings in the attempt of reaching desired destinations.[101] Our main measure of geographic relatedness is based on inverse geographic distance between countries. Proximities are calculated on the basis of shapefiles, retrieved from the Integrated Public Use Microdata Series (IPUMS). We threshold the matrix at a percentile of proximity, in order to guarantee a level of maximum sparseness that doesn't create isolated countries (so that matrix row sums are always above zero). This threshold occurs to be at the 80th percentile of inverse distance for this dataset.

Linguistic proximity: Our second dimension of interaction is based on linguistic proximity. Linguistic barriers are important factors of migrants' mobility (Adsera & Pytlikova, 2015). In this sense, countries may consider themselves as closer substitutes from the perspective of migrants arrivals, if they share a similar language. More generally, linguistic proximity can also be interpreted as a proxy for cultural proximity or similarity in institutions (as in Arbia et al., 2010). We employ data from Melitz and Toubal, 2014 on linguistic proximity between countries. The index developed by the authors ranges from 0 and 1, where 0 indicates the absence of language similarities. A comparable approach, in a different context is found in Debarsy and Ertur, 2019, who also propose the use of this dimensions as an alternative interaction matrix in a spatial econometrics approach to estimate a growth model. Similarly to the authors approach, we normalize the cell values by the sum of the proximity indices of every pair in the data. In particular, define CL_{ij} as the Common Language Index (CL) by Melitz and Toubal, 2014 between countries i and j. Proximity between i an j, for $i \neq j$, is defined as $\frac{CL_{ij}}{\sum_{i \neq j} CL_{ij}}$. Akin to what done for the geographic dimension, we threshold the values to have a maximum level of sparsity, without creating isolated countries. This implies setting values to zero for distances above the 50th percentile.

As Kelejian and Prucha, 2010 advise against row normalization, we perform a spectral normalization on interaction matrices, so that we preserve the properties of the original interaction matrix.[102]

To visualise these interactions, resulting matrices are plotted in the chord diagrams of Figure 3.4.4. To understand how distinct are these two dimensions, we check the degree of correlation between the two matrices. Let W_1 represent the interaction matrix based on geographic proximity and W_2 be the one based on linguistic proximity. Our procedure is as follows: we multiply W_1 times a standard normal variable $u \sim N(0, 1)$, and do the same for W_2. Then we compute the correlation

[101] Cimade, 2018

[102] Note, however, that in our estimates that do not include interactive fixed effects we adopt Lee and Yu, 2010b's estimator. In this case, the presence of time fixed effects leads in the authors' methods to a data transformation that requires row-normalization. Hence, we row-normalize matrices when applying this estimator.

Table 3.4.2: List of countries

Countries:	Belgium Czech Republic Denmark Estonia France Germany Ireland Italy Latvia Lithuania Luxembourg
.	Malta Netherlands Norway Poland Portugal Romania Slovakia Slovenia Spain Sweden Switzerland United Kingdom

List of countries in the Panel

between $W_1 u$ and $W_2 u$ as suggested in J. P. LeSage and Pace, 2014. We repeat for 1000 replications and find on average a correlation coefficient of 0.51 with a standard deviation of 0.18. We conclude that although there's a clear overlapping between the two matrices, there's also enough variation to consider the two as separately meaningful.

(a) Geographic proximity **(b)** Linguistic proximity

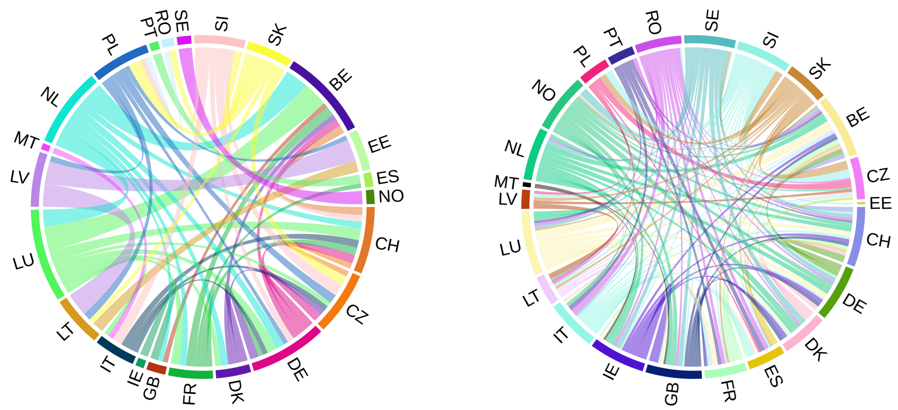


Figure 3.4.4: Interaction matrices, chord diagrams

Notes: Chord diagrams for interaction matrices. These pictures represent the dyadic interactions between countries, presented for a) geographic proximity and b) linguistic proximity. Countries' two digits codes are reported on the sides of the circles. Matrices are symmetric, due to the chosen normalization.

3.5 Empirical setting

We estimate the spatial effects in the asylum policy for Europe, for the period 2013 to 2019 via Shi and Lee, 2017's estimator as detailed in equation 3.1. We focus on numerical observables to indicate the degree of countries response to the European asylum crisis, namely acceptance rates and processing speed.

Spatial relations are determined by interaction matrices W, corresponding to one of two dimension considered: i.e. geographic proximity and language proximity. Vector X_{it} corresponds to the set of covariates in the model. Namely, it includes the country's gdp per capita, unemployment rate, social protection expenditures, population, stocks of foreign population, a dummy indicating that a populist government is in power, all being lagged one time period, to allow one period . The contemporaneous number of applications also enters the equation, as well as the count of displaced people and its value interacted with a dummy for a country belonging to a gateway employed by migrants to access Europe.

Finally, we include a dummy for Germany in the second half of 2015. This period corresponds to Chancellor Merkel's announcement on the propensity of Germany to receive asylum seekers. See Table 3.B.2 for the full details of variables sources and characteristics, while summary statistics are presented in table 3.B.1.

3.5.1 Results

Acceptance rates

Our key results on acceptance rates are summarized in Table 3.5.1, which shows estimates of the spatio-temporal parameters. Complementing this table, figures 3.5.1 and 3.5.2 graph impulse response functions for some key variables. Additionally, full coefficients estimates are reported in tables 3.B.3 and 3.B.4. Specifically, Table 3.B.3 serves as a source of comparison and presents results from a non-spatial, within estimator (column 1), a spatial autoregressive (SAR) model in column 2, a spatial durbin model (SDM) in column 3. Column 4 an 5 show estimates from a SPDP model which disregards interactive effects, for which we adopt Lee and Yu, 2010b's bias-corrected QML estimator.[103] Column 4's interaction matrices are based on geographic proximity, whilst column 5's results are based on linguistic proximity. The left hand side of Table 3.5.1 reports results where interactions are considered on the geographic dimension (columns 1 to 3), while results based on linguistic proximity are reported on columns 4 to 6, on the right section.

In the first column of Table 3.5.1, we introduce estimation results from a SPDP specification, which disregards the interactive effects. Results from this specification pertain to Lee and Yu, 2010b's estimator.[104] We compare these estimates with outcomes of column 2, where interactive effects are considered, following Shi and Lee, 2017. Lastly, column 3 disaggregates the results of column 2 by focusing on origin groups of asylum seekers coming from high-recognition countries. Columns 4 to 6 repeat the same structure, while considering linguistic proximity as the interaction of interest.

In all specifications, we test for the model's stability as suggested in P. Elhorst et al., 2013; Lee and Yu, 2010a. As the authors highlight, restriction $\rho+\lambda_1+\lambda_2 < 1$ must hold for an SPDP spatial model may to be applied as is (else, the model could still be applied, under some data transformation). We also test for the significance of the sum $\lambda_1 + \lambda_2$. We do this to check for possibly jointly significant spatial effects, in case of the parameters being individually insignificant. To construct confidence bounds around these statistics, which we report at a 10% confidence level, we simulate 1000

[103] In these specifications, row-normalization for interaction matrices is recommended and we therefore adopt this alternative normalization.

[104] We row-normalize the interaction matrices for these specifications, as recommended by the authors.

repetitions given the maximum likelihood estimates of the parameters and their variance-covariance matrix. We also take this approach to construct confidence intervals for other restrictions tested, and to obtain lower and upper bounds around the direct and indirect effects (this last is the suggested method in J. LeSage and Pace, 2009 for ML estimators).

Below these test results, we report the number of factors estimated. For consistency to hold, the number of factors should not be underestimated. At the same time, Shi and Lee, 2017 also highlight that for efficiency purposes, factors shall also not be overestimated, which is especially crucial with samples of more moderate sizes like ours. Because condition NC1 from the authors' estimator doesn't hold for us, we cannot use the factor selection criteria proposed by Shi and Lee, 2017.[105] To select the number of factors, we adopt the *Growth Ratio* criterion (GC) of Ahn and Horenstein, 2013. Upon establishing a maximum number of factors r_{max} assumed to be higher than the true number r*, we compute GC on the consisisistent but possibly inefficient model residuals. GC criterion selects $r \leq r_{max}$ factors, where r maximizes argument of equation 3.2:

$$GC = \frac{log(V(r-1)/V(r))}{log(V(r)/V(r+1))} \tag{3.2}$$

Where $V(r) = \frac{1}{NT}\sum_{r+1}^{N} \mu_i(D_{NT}D'_{NT})$, D_{NT} are the model residuals where r_{max} is set as maximum number of factors and μ_i is the ith largest eigenvalue associated with the matrix in its argument.[106] In column 1 estimates, the spatial parameters are never significant. Stability holds only marginally, as the bounds of $\rho + \lambda_1 + \lambda_2$ marginally include 1.

Results are quite different when strong cross-sectional dependence is accounted for: in column 2, we find significant presence of spatial correlation, resulting from both λ_1 and λ_2. Size-wise, λ_1 is negative and λ_2 is positive, meaning a simultaneous negative spatial correlation that reverses in the next periods. In both column 1 and column 2, the time parameter is strongly significant and positive, with a similar size of respectively ∼0.598 and ∼0.615. In column 3, we disaggregate these results, focusing on acceptance rates from high-recognition origins. In this case, we find that for high-recognition origins, the time parameter is smaller in size. The spatial coefficients follow similar signs, with some size fluctuation.

The presence of strong cross-sectional dependence appears to deflate the role of the spatial dimension in column 1.[107]

[105] We rely on the alternative NC2 for the identification of the number of factors.

[106] We select r_{max}=15. We follow Ahn and Horenstein, 2013 and doubly demean our data in our factors' selection procedure. Else, the criteria may tend to overly predict one factor in some circumstances.

[107] Its presence is also detected Pesaran, 2015's test for strong cross-sectional (CD) dependence, which we apply to the residuals of the within-estimator (test results are at the bottom of column 1, in table 3.B.3). The test's null hypothesis is that CD dependence is weak, i.e. the correlation between units goes to zero as N goes to infinity. Compared against the alternative of strong cross-sectional dependence (CD). The test results suggest there's strong CD in the data.

For SPDP models, interpretating coefficients is not directly meaningful. We follow Debarsy et al., 2012 to compute marginal effects over time, which we report visually in figures 3.5.1 and 3.5.2. In the graphs, we also partition the average indirect effects over the whole dataset, from indirect effects on first neighbors (line in magenta). We do that using a simplification suggested in Parent and LeSage, 2010 and applied in Debarsy et al., 2012, which we can perform on the condition that the restriction $-\rho * \lambda_1 = \lambda_2$ holds. By testing for this restriction, we present this additional line in magenta whenever this equality cannot be rejected with 90% confidence.

Figure 3.5.1 reports the impulse response function for acceptance rates, i.e. the response T-periods ahead in the acceptance rates resulting from exogenous positive shock on the acceptance of country i. Subfigure a shows results pertaining to acceptance rates for all origins, whilst results in subfigure b are specific for high-recognition origins. The graph suggests that an exogenous shock on overall acceptance rates of a country implies a decrease in acceptance in other countries in the dataset (red line). The blue line represents direct effects of the same shock on country i.[108]

Negative spatial correlation suggests that countries are strategic substitutes in recognition responses. A positive shift in a country's acceptance rates decreases the acceptance of its geographic neighbors, in such a way to limit attraction from flows of migrants potentially spilling over. Interestingly, when we disaggregate the acceptance patterns focusing on highly recognized origins, we find that a positive spatial correlation emerges in acceptance rates at $t > 0$. In Görlach and Motz, 2021's model, strategic substitution and complementarity may both emerge in the reception of asylum seekers, depending on two co-occurring mechanisms.

On the one side, a rise in the acceptance rate of a country may increase the inflows to that country, thus reducing the reception costs to its neighbors that could then engage in a similar choice. On the other side, the same rise in acceptance rates of one destination may provoke more transits of migrants overall, and/or in the areas around the country, so that neighbors that want to prevent leakages of applications into their territory would decrease their reception. In our finding, countries react to decrease the likelihood of leakages, thus limiting acceptance whenever neighbors increase theirs. At $t > 0$, however, for origins of high-recognition, a diffusion effect appears. A potential mechanism may be a learning effect, through which origins most accepted by neighbors are signaled as most widely acceptable. The indirect effect of a country's acceptance reverts back after two periods, while the positive effect for high-recognition origins is more persistent. Models that do not consider dynamics may fail to capture these long-lasting cross-country effects of government choices.

We present results with our alternative interaction matrix in columns 4 to

[108] Direct effects also reflect the role of feedback, capturing the idea that the impact propagates back to the original country where the shock took place.

6 of Table 3.5.1. When considering linguistic proximity, outcomes are relatively comparable for overall acceptance patterns: we find again that not accounting for the effects of common factors underestimates the absolute degree of spatial correlation. A negative spatial auto-correlation enters through λ_2 in column 4 at 10% level of significance. Once interactive effects are accounted for (column 5), we find countries to be strategic substitutes, with the effect being immediate at time 0 and absorbing out at t+1. For high-recognition origins, we find similar patterns to those based on geographic proximity: the size of rho decreases and the diffusion effect appears at $t > 0$.

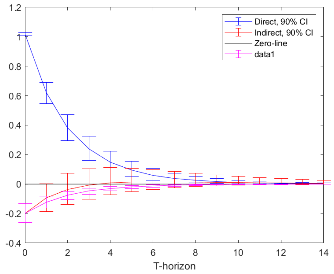
Table 3.5.1: SPDP Model, acceptance rate, benchmark result summary

	Geographic proximity			**Linguistic proximity**		
	No factors	***With factors***		***No factors***	***With factors***	
	Overall	*Overall*	*High-recognition*	*Overall*	*Overall*	*High-recognition*
ρ	0.5983***	0.6152***	0.2314***	0.6221***	0.6377***	0.1738***
	(0.0355)	(0.032)	(0.0365)	(0.035)	(0.0338)	(0.0389)
λ_1	0.0009	-0.3906***	-0.1652*	0.0023	-0.3179**	-0.5211***
	(0.049)	(0.0917)	(0.0866)	(0.0976)	(0.1242)	(0.1339)
λ_2	0.0095	0.2977**	0.3481***	-0.2109*	0.3191**	0.4934***
	(0.0656)	(0.1207)	(0.1109)	(0.1225)	(0.1607)	(0.1141)
Obs	621	644	644	621	644	644
$\rho + \lambda_1 + \lambda_2$	[0.495, 0.733]	[0.287, 0.777]	[0.151, 0.694]	[0.209, 0.62]	[0.349, 0.934]	[-0.176, 0.496]
$\lambda_1 + \lambda_2$	[-0.085, 0.119]	[-0.3, 0.117]	[-0.043, 0.425]	[-0.394, -0.027]	[-0.263, 0.253]	[-0.292, 0.259]
Factors	**X**	✓	✓	**X**	✓	✓
Nr factors	NA	ER:1; GR:1	ER:1; GR:1	NA	ER:1; GR:1	ER:7; GR:7
Controls: Economic	✓	✓	✓	✓	✓	✓
Controls: Political	✓	✓	✓	✓	✓	✓
Controls: Demographic	✓	✓	✓	✓	✓	✓

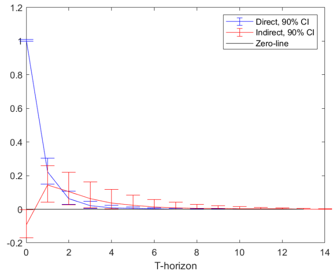
Notes: standard errors in parentheses. These results correspond to regression estimates for for our baseline model on acceptance rates. Interaction matrices considered are based on geographic neighbors (column 1 to 3) and linguistic neighbors (column 4 to 6). Column 1 and column 4 show estimates for an SPDP model that doesn't include interactive effects. For these regressions, we apply the QML estimator of Lee and Yu, 2010b. Their bias-corretion transformation reduces the sample size (hence the lower N in these columns) and requires row-normalization. Interactive effects are included in column 2 to 3, and 5 to 6. Columns 3 and 6 zoom into acceptance rates for highly accepted origins, whilst for all other columns, overall patterns are considered. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Below these statistics, we report the number of estimated factors, following criterion GC. In these regressions, we control for the full set of economic, political and demographic covariates. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Figure 3.5.1: Acceptance rates, impulse-response

Geographic proximity

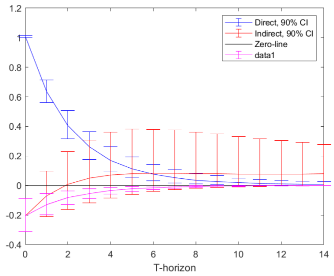


(a) Overall

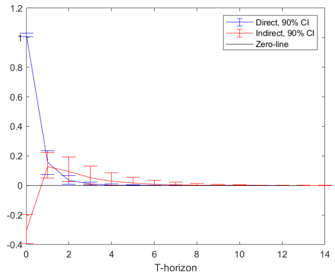


(b) High-recognition origins

Linguistic proximity



(c) Overall



(d) High-recognition origins

Notes: Impulse-response graphs on acceptance rates. These graphs represent the impact over time from an exogenous shock in the acceptance rate of a country, on the acceptance rates of the country itself (blue line), the average indirect effects onto other countries (red line) and, when an additional restriction allows, the indirect effects on the countries' first neighbors (magenta line). The top side of the graph represents effects based on geographic proximity, whilst results for linguistic proximity are shown on the bottom. On the left, results pertain to overall acceptance rates, while on the right, we plot results for a subset of origins with high recognition rates. We report effects for an horizon of 15 periods, starting with the simultaneous results at t=0. 10% confidence intervals are reported around the point estimates.

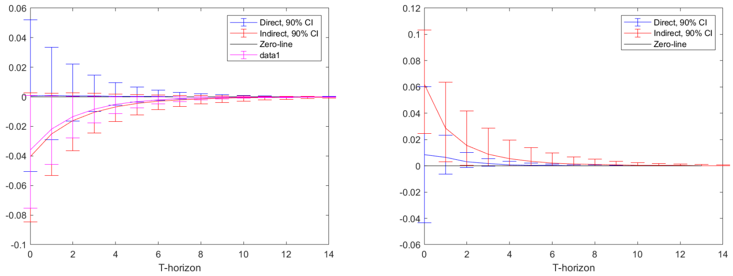
Finally, we use the model estimates to describe the direct and indirect role of migrants arrivals at the external borders, on cross-country acceptance rates. We focus on this covariate as we consider the waves of arrivals to be more unintended, and at least to some extent not directly controlled by the individual decisions of one European country. As presented for the spatial parameters, we look into impulse-response graphs for the sake of readability.[109] In Figure 3.5.2, we see that the arrivals at the border decrease overall acceptance rates of geographic neighbors (subfigure a), while no effect is found for linguistic neighbors. Results differ when considering acceptance rates of high-recognition origins. For this subset of countries featuring high recognition rates at arrival, acceptance rates grow for geographic neighbors. We interpret this as evidence that countries would condition their

[109] We also present short-term and long-term direct and indirect effects as a complement, in table 3.B.9, as calculated for instance in Belotti et al., 2013 and J. P. Elhorst, 2014.

strategic reactions upon the perceived legitimacy of the asylum requests, as proposed in Bertoli et al., 2022 and Guichard, 2020. As both studies suggest, for some receiving destinations, countries of origin identified as safer would lead to denied asylum.

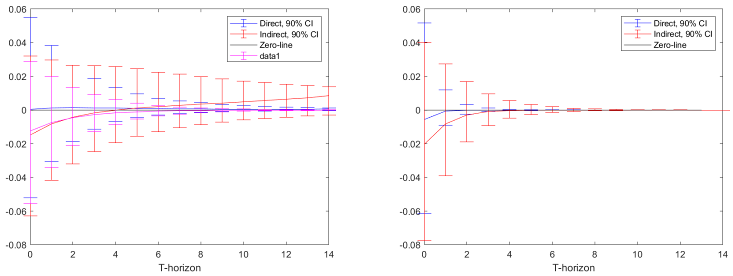
Figure 3.5.2: Effect of migrants arrivals at external borders on acceptance

Geographic proximity



(a) Overall **(b)** High-recognition origins

Linguistic proximity



(c) Overall **(d)** High-recognition origins

Notes: Impulse-response graphs showing the effects of migrants arrivals at the external EU borders on acceptance rates. These graphs represent the impact over time from an exogenous shock in the arrival of migrants at the external EU borders, on the acceptance rates of the country itself (blue line), the average indirect effects onto other countries (red line) and, when an additional restriction allows, the indirect effects on the countries' first neighbors (magenta line).The top side of the graph represents effects based on geographic proximity, whilst results for linguistic proximity are shown on the bottom. On the left, results pertain to overall acceptance rates, while on the right, we plot results for a subset of origins with high recognition rates. We report effects for an horizon of 15 periods, starting with the simultaneous results at t=0. 10% confidence intervals are reported around the point estimates.

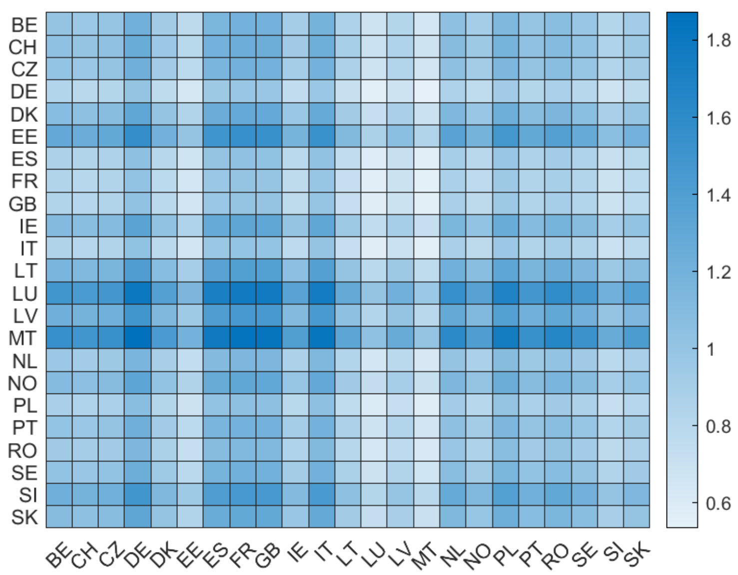
Extended results on acceptance

Evidence in trade studies suggest that smaller countries display higher levels of integration (see for example Alesina et al., 2005). Drawing a parallel into our setting, it is possible that cross-country influence is stronger from bigger to smaller countries, meaning that the decisions of big countries matter more for smaller countries, whilst countries of higher size are reasonably more independent. This asymmetry in countries influences could result from international pressures exerted by country-leaders, from international soft-power mechanisms, or it could also reflect from an higher economic integration that spills over to other dimensions of decision-making. Additionally, it could result from a higher internal political pressure represented by a larger electorate size. To account for this possibility, we propose an additional set of results, in which the relative size of countries matter for their influence. Our new interaction matrix would be $\hat{W}$, with cells $\hat{w}_{ij}$ defined as:

$$\hat{w}_{ij} = \frac{log(pop_j)}{log(pop_i)} w_{ij} \tag{3.3}$$

Where w_{ij} is simply the original interaction matrix cell. In other words we weight the original interaction matrices by the relative size of units i and j, expressed as the ratio of the logs of their populations. Population data refer to the initial sample period t=1. To better understand these relations, we show in Figure 3.5.3 the heatmap of relative population weights. As the picture shows, countries with smaller population size, such as Luxembourg, Malta, and the Baltic republics, have darker rows, as their spatial relations are now allowed to have more importance. On the contrary, bigger countries, such as France, Germany and Italy, show relatively lighter colors in their rows, as they're now allowed to have relatively more independence. The opposite holds looking into columns: smaller countries are allowed to have lower influence, vis à vis larger ones.

Figure 3.5.3: Heatmap, population weights



Notes: Heatmap of country weights, where entries in row i, column j correspond to weight $\frac{log(pop_j)}{log(pop_i)}$.

Results for this alternative specification are shown in Table 3.5.2. The top part of the table is based on geographic proximity, while the bottom one presents results on the linguistic proximity alternative. Column 1 reports the baseline results for comparison, and columns 2 to 4 display the specification based on relative population sizes. Progressively from left to right, we assign more importance to the ratio of populations, using the powers of 1.5, 2 and 2.5 respectively. We find results for acceptance rates to be quite similar across these model versions. In the geographic proximity results, all time and space parameters are practically identical to the baseline ones. When considering linguistic interactions, similar parameter values are estimated, with the exception of λ_2 that is negative and insignificant for column 2. This suggests that the negative contemporaneous spatial effect will reabsorb less quickly under this result.

Despite these considerations, we do not find sizeable differences upon the use of this alternative. Note that although we do not find evidence that small countries are more spatially dependent than big countries, this doesn't mean that small countries may not have idiosyncratic difference responses in terms of acceptance rates. With respect to common shocks, small countries may react more strongly, and may generally follow different protocols than larger countries. In this case, these (non-spatial) heterogeneities would be captures in our interactive effects term, and go beyond the interest of this study.

Table 3.5.2: SPDP Model, acceptance rate, weighting by population

	Geographic proximity			
	Baseline	***Population weights***		
		$(\frac{lpop_i}{lpop_j})$	$(\frac{lpop_i}{lpop_j})^{1.5}$	$(\frac{lpop_i}{lpop_j})^{2}$
ρ	0.6152***	0.6252***	0.6315***	0.6369***
	(0.032)	(0.0318)	(0.0317)	(0.0316)
λ_1	-0.3906***	-0.4141***	-0.4105***	-0.3948***
	(0.0917)	(0.0893)	(0.086)	(0.0811)
λ_2	0.2977**	0.3303***	0.3371***	0.3355***
	(0.1207)	(0.1215)	(0.1173)	(0.1104)
Obs	644	644	644	644
$\rho + \lambda_1 + \lambda_2$	[0.326, 0.734]	[0.335, 0.734]	[0.371, 0.75]	[0.392, 0.75]
$\lambda_1 + \lambda_2$	[-0.273, 0.105]	[-0.267, 0.093]	[-0.257, 0.107]	[-0.231, 0.094]
Conc. Log-lik	2.144	2.1424	2.1413	2.14
Factors	✓	✓	✓	✓
Nr factors	ER:1; GR:1	ER:1; GR:1	ER:1; GR:1	ER:1; GR:1
Controls: Economic	✓	✓	✓	✓
Controls: Political	✓	✓	✓	✓
Controls: Demographic	✓	✓	✓	✓
	Linguistic proximity			
	Baseline	***Population weights***		
		$(\frac{lpop_i}{lpop_j})$	$(\frac{lpop_i}{lpop_j})^{1.5}$	$(\frac{lpop_i}{lpop_j})^{2}$
ρ	0.6377***	0.5931***	0.6138***	0.6076***
	(0.0338)	(0.0349)	(0.0343)	(0.0344)
λ_1	-0.3179**	-0.3847***	-0.3827***	-0.4005***
	(0.1242)	(0.1263)	(0.12)	(0.1144)
λ_2	0.3191**	-0.1082	0.3427**	0.323*
	(0.1607)	(0.217)	(0.1706)	(0.1659)
Obs	644	644	644	644
$\rho + \lambda_1 + \lambda_2$	[0.398, 0.898]	[-0.279, 0.472]	[0.302, 0.824]	[0.229, 0.798]
$\lambda_1 + \lambda_2$	[-0.224, 0.238]	[-0.844, -0.149]	[-0.293, 0.203]	[-0.351, 0.169]
Conc. Log-lik	2.1221	2.12	2.1289	2.1307
Factors	✓	✓	✓	✓
Nr factors	ER:1; GR:1	ER:1; GR:1	ER:1; GR:1	ER:1; GR:1
Controls: Economic	✓	✓	✓	✓
Controls: Political	✓	✓	✓	✓
Controls: Demographic	✓	✓	✓	✓

Notes: standard errors in parentheses. These results present estimates for acceptance rates. Geographic proximity matrices are used on the top, and linguistic proximity is considered on the bottom part. Column 1 reports baseline results, while columns 2 to 4 show results where interaction matrices are weighted by relative population From left to right, we augment the importance of our population weights as indicated at the top of the column. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Below these, we add the resulting concentrated log-likelihood and the number of estimated factors, following the growth ratio (GR) criterion. We also report the number of factors suggested by the Eigenvalue ratio (ER), for completeness. In these regressions, we control for the full set of economic, political and demographic covariates. Stars correspond to the following p-values: * p < .10, ** p < .05, *** p < .001.

3.5.2 Processing speed

As a second piece of evidence, we look at processing speed, measured as the count of decisions over the count of applications. As done above for acceptance rates, spatial estimates are summarized in Table 3.5.3, which shows results for spatio-temporal parameters. We complement this summary with full coefficients estimates, reported in tables 3.B.5 and 3.B.6. Again, the tables' structure is identical to what presented on acceptance rates, with the left section of Table 3.5.3 showing results for the geographic dimension (columns 1 to 3), and columns 4 to 6 displaying coefficients the linguistic one on the right section.

In column 1 estimates, we find evidence of a positive spatial autocorrelation, entering for λ_1. Again, results differ when strong cross-sectional dependence is controlled for: in column 2, find a negative contemporaneous spatial correlation, which however reverts in time ($\lambda_2 > 0$). In both columns, the time parameter is strongly significant and positive, with the size of ρ being higher in column 2 ($\sim$0.395 and $\sim$0.629 in columns 1 and 2, respectively). In column 3, when we focus on processing speed for high-recognition origins, we do not find evidence of spatial correlation, suggesting that overall results are mainly driven by origins where recognition was less likely to be guaranteed. All in all, accounting for interactive effects reduces the degree of positive spatial correlation in processing speed, which is overestimated when the heterogeneous impacts of common factors are not accounted for.

When looking into linguistic proximity, we find overall a similar pattern of results: a negative contemporaneous spatial correlation emerges, if we allow for interactive effects. Here however, λ_2 is not statistically significant, and rho is smaller in size, which leads to a slightly different dynamic than for geographic relations. We consider these findings in light of the diversion mechanism highlighted in Görlach and Motz, 2021. If countries relax their reception procedures, these destinations may now become more attractive for migrants that may benefit from lower processing efficiency, i.e. those for which acceptance is less likely guaranteed. As a response, neighbors of these countries may now speed up their processes to avoid that the attraction of such inflows doesn't spill over to their jurisdiction.

Table 3.5.3: SPDP Model, processing speed, benchmark result summary

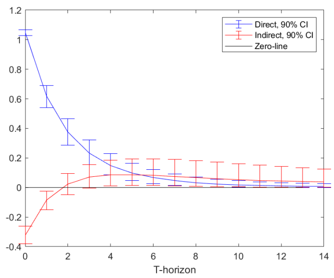
	Geographic proximity			Linguistic proximity		
	No factors	*With factors*		*No factors*	*With factors*	
	Overall	*Overall*	*High-recognition*	*Overall*	*Overall*	*High-recognition*
ρ	0.3595***	0.629***	0.3636***	0.4267***	0.2095***	0.3813***
	(0.0395)	(0.0316)	(0.0402)	(0.0378)	(0.0427)	(0.0394)
λ_1	0.2436***	-0.693***	0.0413	0.2353	-0.6233***	0.1319
	(0.0941)	(0.0874)	(0.0804)	(0.1477)	(0.137)	(0.0895)
λ_2	0.0709	0.7331***	-0.0502	0.1614	-0.0297	-0.0246
	(0.067)	(0.1011)	(0.0616)	(0.1391)	(0.1072)	(0.066)
Obs	621	644	644	621	644	644
$\rho + \lambda_1 + \lambda_2$	[0.57, 0.789]	[0.422, 0.905]	[0.153, 0.553]	[0.602, 1.032]	[-0.778, -0.095]	[0.278, 0.698]
$\lambda_1 + \lambda_2$	[0.208, 0.436]	[-0.149, 0.217]	[-0.164, 0.136]	[0.184, 0.607]	[-0.944, -0.345]	[-0.057, 0.262]
Factors	**X**	✓	✓	**X**	✓	✓
Nr factors	NA	ER:6; GR:6	ER:2; GR:2	NA	ER:1; GR:6	ER:2; GR:2
Controls: Economic	✓	✓	✓	✓	✓	✓
Controls: Political	✓	✓	✓	✓	✓	✓
Controls: Demographic	✓	✓	✓	✓	✓	✓

Notes: standard errors in parentheses. These results correspond to regression estimates for our baseline model on processing speed. Interaction matrices considered are based on geographic neighbors (column 1 to 3) and linguistic neighbors (column 4 to 6). Column 1 and column 4 show estimates for an SPDP model that doesn't include interactive effects. For these regressions, we apply the QML estimator of Lee and Yu, 2010b. Their bias-corretion transformation reduces the sample size (hence the lower N in these columns) and requires row-normalization. Interactive effects are included in column 2 to 3, and 5 to 6. Columns 3 and 6 zoom into processing speed for highly accepted origins, whilst for all other columns, overall patterns are considered. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Below these statistics, we report the number of estimated factors, following the growth ratio (GR) criterion. We also report the number of factors suggested by the Eigenvalue ratio (ER), for completeness. In these regressions, we control for the full set of economic, political and demographic covariates. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

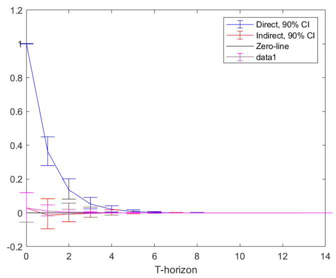
For both dimensions, we show impulse-response functions from an exogenous shock in processing speed in Figure 3.5.4. As suggested in the table results, the graphs show a negative indirect effect in overall processing speed led by an exogenous rise in the speed of one country. This effect reverts to being marginally positive at $t > 0$ when geographic proximities are considered, while it reverts to 0 in around 3 periods when interaction matrices are based on the linguistic channel. As pre-announced from the table results, for high-recognition origins, we do not observe significant indirect effects.

Figure 3.5.4: Processing speed, impulse-response

Geographic proximity

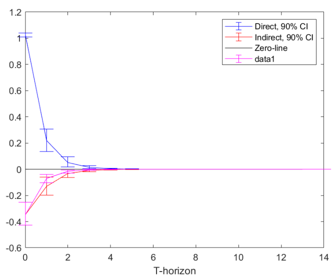


(a) Overall

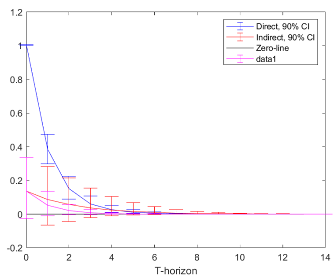


(b) High-recognition origins

Linguistic proximity



(c) Overall



(d) High-recognition origins

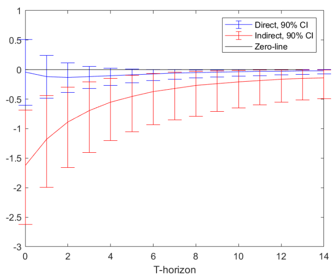
Notes: Impulse-response graphs on processing speed. These graphs represent the impact over time from an exogenous shock in the rate of processing of a country, on the processing speed of the country itself (blue line), the average indirect effects onto other countries (red line) and, when an additional restriction allows, the indirect effects on the countries' first neighbors (magenta line). The top side of the graph represents effects based on geographic proximity, whilst results for linguistic proximity are shown on the bottom. On the left, results pertain to overall speed of processing, while on the right, we plot results for a subset of origins with high recognition rates. We report effects for an horizon of 15 periods, starting with the simultaneous results at t=0. 10% confidence intervals are reported around the point estimates.

We conclude the analysis of this section, by zooming into the effects of two key covariates: i) the role of Germany's announcement regarding its propensity to receive migrants; ii) the role of migrants' arrivals at the external EU borders in the speed of processing applications.[110]

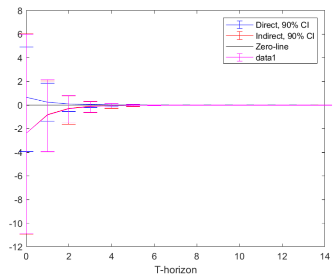
Graph 3.5.5 shows the first impact of interest. We find that Germany's declared intent significantly decreased the number of decisions, weighted by the number of applications, in the neighboring countries, for both geographic and linguistic neighbors. Regarding persistency, this is found to be greater, for the case of indirect effects based on geographic interactions. The effect however appears to be driven by origins of lower recognition, as the same impact is not present for high-recognition origins. A possible interpretation of this result is that the declared intent of Germany to take a proactive and open role led to a rilief of connected countries, which lowered their efficiency.

Figure 3.5.5: Germany's announcement effect on processing speed

Geographic proximity

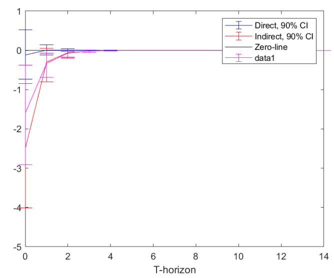


(a) Overall

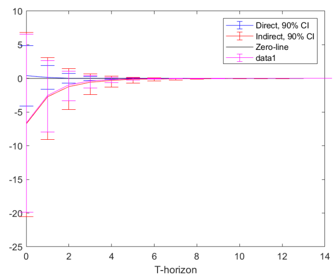


(b) High-recognition origins

Linguistic proximity



(c) Overall



(d) High-recognition origins

Notes: Impulse-response graphs showing the effects of Germany's annoucement on their propension to receive asylum seekers, on the speed of processing asylum requests. The self-country impact is shown on the blue line, while the average indirect effects onto other countries are represented by the red line and, when an additional restriction allows, we show the indirect effects on the countries' first neighbors in magenta. The top side of the graph represents effects based on geographic proximity, whilst results for linguistic proximity are shown on the bottom. On the left, results pertain to overall processing speed, while on the right, we plot results for a subset of origins with high recognition rates. We report effects for an horizon of 15 periods, starting with the simultaneous results at t=0. 90% confidence intervals are reported around the point estimates.

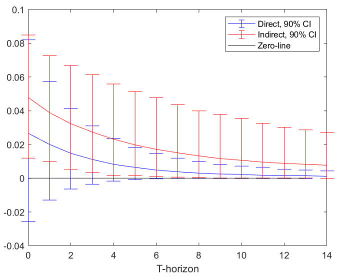
Graph 3.5.6 shows impulse-response functions plotting the effects of arrivals at

[110] For acceptance rates we haven't presented the first effect, because we do not find a significant role for Germany's announcement in decreasing or increasing indirectly acceptance rates cross-country. Therefore, for conciseness, we only described significant findings.

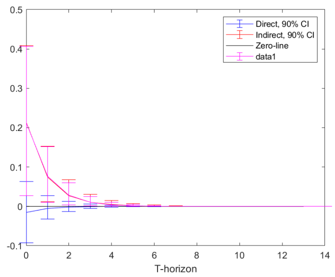
the borders. We find that arrivals at the borders had an indirect positive effect on the speed of processing asylum requests. This effect is present in both overall and high-recognition origins and for both interaction matrices. This finding suggests that the potential leakage of migrants transiting from the external EU borders induced neighoring countries to undertake decisions more quickly. For these arrivals, we also observed an indirect decrease in acceptance rates for geographic neighbors, indicating that higher efficiency was associated with the desire of countries to accelerate the processing for valid and invalid requests, thus reducing the costs of an elongated reception.

Figure 3.5.6: Effect of migrants arrivals at external borders on processing speed

Geographic proximity

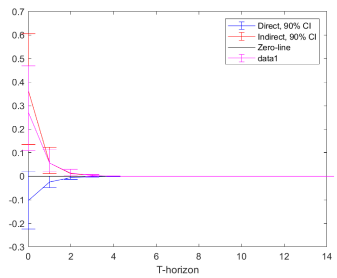


(a) Overall

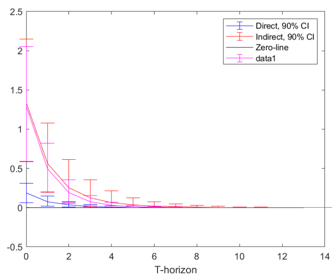


(b) High-recognition origins

Linguistic proximity



(c) Overall



(d) High-recognition origins

Notes: Impulse-response graphs showing the effects of migrants arrivals at the external EU borders on processing speed. These graphs represent the impact over time from an exogenous shock in the arrival of migrants at the external EU borders, on the processing speed of the country itself (blue line), the average indirect effects onto other countries (red line) and, when an additional restriction allows, the indirect effects on the countries' first neighbors (magenta line).The top side of the graph represents effects based on geographic proximity, whilst results for linguistic proximity are shown on the bottom. On the left, results pertain to overall processing speed, while on the right, we plot results for a subset of origins with high recognition rates. We report effects for an horizon of 15 periods, starting with the simultaneous results at t=0. 10% confidence intervals are reported around the point estimates.

Extended results on processing speed

Similarly to what presented for acceptance rates, we proceed to test whether spatial relations in processing speed depend on the relative size of countries. We sum up the main results in Table 3.5.4. Again, the top part of the table is based on geographic proximity, while the bottom one presents results on the linguistic proximity alternative. Column 1 reports the baseline results for comparison, and columns 2 to 4 display the specification based on relative population sizes. Different columns display different levels of importance to the ratio of populations, using the powers of 1.5, 2 and 2.5 respectively, to the formula of equation 3.3. Again, we find results to be relatively similar across these specifications. As a minor difference, we see the dynamics being slightly different in the geographic proximity results. λ_2 loses significance and ρ decreases in value in columns 3 and 4, suggesting a higher persistency of the cross-country influence in smaller countries.

Table 3.5.4: SPDP Model, processing speed, weighting by population

	Geographic proximity			
	Baseline	***Population weights***		
		$(\frac{lpop_i}{lpop_j})$	$(\frac{lpop_i}{lpop_j})^{1.5}$	$(\frac{lpop_i}{lpop_j})^2$
ρ	0.629***	0.6227***	0.1206***	0.1259***
	(0.0316)	(0.0323)	(0.0412)	(0.0412)
λ_1	-0.693***	-0.711***	-0.7648***	-0.6798***
	(0.0874)	(0.0847)	(0.0767)	(0.0753)
λ_2	0.7331***	0.6971***	0.1304	0.0962
	(0.1011)	(0.098)	(0.0817)	(0.0752)
Obs	644	644	644	644
$\rho + \lambda_1 + \lambda_2$	[0.488, 0.841]	[0.438, 0.78]	[-0.73, -0.29]	[-0.661, -0.252]
$\lambda_1 + \lambda_2$	[-0.119, 0.185]	[-0.153, 0.126]	[-0.812, -0.453]	[-0.766, -0.42]
Conc. Log-lik	1.4776	1.4817	1.5249	1.5268
Factors	✓	✓	✓	✓
Nr factors	ER:6; GR:6	ER:6; GR:6	ER:6; GR:6	ER:6; GR:6
Controls: Economic	✓	✓	✓	✓
Controls: Political	✓	✓	✓	✓
Controls: Demographic	✓	✓	✓	✓
	Linguistic proximity			
	Baseline	***Population weights***		
		$(\frac{lpop_i}{lpop_j})$	$(\frac{lpop_i}{lpop_j})^{1.5}$	$(\frac{lpop_i}{lpop_j})^2$
ρ	0.2095***	0.143***	0.1371***	0.135***
	(0.0427)	(0.0434)	(0.0431)	(0.043)
λ_1	-0.6233***	-0.6498***	-0.6698***	-0.6956***
	(0.137)	(0.1288)	(0.1251)	(0.12)
λ_2	-0.0297	0.032	0.0517	0.0648
	(0.1072)	(0.0986)	(0.096)	(0.0931)
Obs	644	644	644	644
$\rho + \lambda_1 + \lambda_2$	[-0.756, -0.117]	[-0.799, -0.175]	[-0.784, -0.202]	[-0.767, -0.205]
$\lambda_1 + \lambda_2$	[-0.937, -0.358]	[-0.902, -0.346]	[-0.891, -0.37]	[-0.88, -0.373]
Conc. Log-lik	1.4558	1.441	1.4415	1.4382
Factors	✓	✓	✓	✓
Nr factors	ER:1; GR:6	ER:1; GR:6	ER:1; GR:6	ER:6; GR:6
Controls: Economic	✓	✓	✓	✓
Controls: Political	✓	✓	✓	✓
Controls: Demographic	✓	✓	✓	✓

Notes: standard errors in parentheses. These results present estimates for processing speed. Geographic proximity matrices are used on the top, and linguistic proximity is considered on the bottom part. Column 1 reports baseline results, while columns 2 to 4 show results where interaction matrices are weighted by relative population From left to right, we augment the importance of our population weights as indicated at the top of the column. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Below these, we add the resulting concentrated log-likelihood and the number of estimated factors, following the growth ratio (GR) criterion. We also report the number of factors suggested by the Eigenvalue ratio (ER), for completeness. In these regressions, we control for the full set of economic, political and demographic covariates. Stars correspond to the following p-values: * p < .10, ** p < .05, *** p < .001.

3.6 Conclusion

In this paper we investigated whether there is an interdependence between countries' asylum policies in Europe. We focus on 23 European countries, for the period 2013 to 2019. As well summarized in Rayp et al., 2017, the economics literature investigating the drivers of migration policies has been relative scarse. This is because migration policies are multi dimensional decisions with a strongly qualitative component, and converting them into unequivocal numerical values doesn't come without challenges (see also De Haas et al., 2015).
Countries may be more or less restrictive in their policies, depending on the target migrant group. We thus focus on a specific target group, which is that of asylum migrants. With Europe facing unprecedented inflows of asylum seeking migrants in the 2010s decade, the public debate got inflamed in several member states, with the theme of immigration gaining political priority (Hutter & Kriesi, 2022). By following Bertoli et al., 2022, we circumvent issues related to quantifying policy measures, by directly exploring numerical outcomes: we focus on acceptance rates and processing speed of asylum applications.

We contribute to the existing literature by adopting a flexible Spatial Dynamic Panel Data model that allows to include both time and space autocorrelation in the policy measures, as well as space dependencies in the explanatory variables. The idea is that if a common system is evenly implemented in Europe, then once we control for the uneven distribution of migrants and their applications, asylum responses of countries should be uniform, instead of following patterns based on geographic (or linguistic/cultural) neighbors. The presence of a spatial effect would therefore proxy strategic decision making, where countries react similarly to their neighbors, rather than uniformly within the common agreement. Similarity and neighborhood may not only be intended geographically (Case et al., 1993; Conley, 1999). In this sense, linguistic proximity can be a salient dimension as it may relate to similar cultural backgrounds and higher international connections, key aspects when considering which countries may be strategic substitutes.

Crucially, in our preferred specifications we factor out strong cross-sectional dependence stemming from heterogenous responses to unobserved common shocks (Pesaran, 2006; Shi & Lee, 2017). This step proves critical for the identification of spatial effects that are otherwise incorrectly estimated. Specifically, we account for interactive fixed effects with Shi and Lee, 2017's estimator, and we estimate the number of omitted factors given a selection criterion by Ahn and Horenstein, 2013. We find that the exclusion of interactive fixed effects biases spatial correlation upwards for both acceptance rates and processing speed.

Countries are found to be strategic substitutes in their asylum policies, i.e. an increase in acceptance rates of one country decreases the acceptance rates of its neighbors, similarly, a negative shock in the processing speed of asylum applications in one country increases the speed of its neighbors. In a parallel with Görlach and Motz, 2021, strategically decreasing acceptance when a neighbor increases it is a response that aims at reducing potential inflows of migrants, now attracted towards the surroundings of the accepting country.

At the same time, countries tend to increase their processing speed in handling applications, when their neighbors relax them. Such a reaction is only present for asylum claims from countries with lower chances of getting accepted. Again here, upon an exogenous negative shock in the speed of processing applications in one country, connected destinations that fear an attraction towards the overall area may increase their speed to prevent the risks and or the costs of receiving spillover inflows. Our key results are present for both geographic and linguistic interaction matrices, while some heterogeneity is found across origins of asylum requesters.

Additionally, we also find evidence that the arrival of migrants at the external EU borders lowers the acceptance rates in geographic neighbors of lower recognition origins and rises their processing speed. We interpret this as a sign of perceived pressures from these arrivals, leading countries to adopt a tightening approach, so to lower reception costs. Despite these reactions, we observe that the declaration of Germany's chancellor in 2015 intended to take up a role in the reception leads related countries to relax their reception speed.

Given the onset of Russian attacks to Ukraine and the presence of climate change risks, asylum migration keeps being a key matter in European economies. Therefore, given this setting, it is particularly important to understand how asylum reception interrelates across member states, both to inform a future harmonization of asylum reception processes and to prevent negative related outcomes. In fact the lack of current actual coordination in the application and reception processes brings a main unfortunate consequence in the form of rising irregular migration, unavoidably fostered by protection seekers in search of better chances to obtain a refugee status across the EU (among most recent contributions on the topic see Czaika & Hobolth, 2016).[111]

A number of further negative outcomes can be favoured by the lack of policy harmonization. Notably these include rising difficulties in the effectiveness of the overall integration process, since the presence of irregular migrants can rise a negative perception of the cultural diversity they bring along, making the group an easy target to blame for minor crimes and perceived social insecurity, most often through a political and media discourse not always mirroring statistical facts (Heidenreich et al., 2019).

Overall this paper contributes in understanding the crucial transmission mechanisms through which more or less restrictive asylum policies spread across Europe, assessing how countries interdepend in the number of asylum seekers which are willing to welcome and in the efficiency of the acceptance process. This is of key im-

[111] For a definition of irregular migration see: https://www.migrationdataportal.org/themes/irregular-migration.

portance in calling for a stronger cooperation plan and its actual implementation, to upfront future challenges. We hope that more research will follow in this direction.

Appendix

3.A Appendix

3.A.1 Additional results

Processing times

Results for processing times measured à la Bertoli et al., 2022 are presented in Table 3.A.1, and complemented by full coefficients estimates in tables 3.B.7 and 3.B.8. The tables' structure is identical to the results presented on acceptance rates. Table 3.A.1 reports estimates where interactions are considered on the geographic dimension (columns 1 to 3), while results based on linguistic proximity are reported on columns 4 to 6, on the right section.

In column 1 estimates, we do not observe a significant spatial autocorrelation. As for our other outcomes, results differ when strong cross-sectional dependence is controlled for: in column 2, we find a significant negative contemporaneous spatial parameter λ_1, with a significant positive λ_2 that shapes the reversion of the negative effects at $t > 0$. In both columns, the time parameter is strongly significant and positive, with a lower size in column 2. Without including for interactive effects, ρ has a point estimate of $\sim$0.871 and once they're controlled for, ρ takes the value of $\sim$0.6424. In column 3, we disaggregate these results, focusing on processing times for high-recognition origins. We find that for high-recognition origins, negative contemporaneous spatial correlation disappears, while λ_2 is positive, suggesting that once again, patterns in asylum reception are not uniform across origins.

When strong cross-sectional dependence is not accounted for, here as well spatial correlation appears more positive, though insignificant. Its presence is again detected by Pesaran, 2015's test for strong cross-sectional (CD) dependence, as seen at the bottom of column 1, in table 3.B.7). For results based on linguistic proximity, we do not find a significant spatial correlation, neither without nor with the inclusion of interactive fixed effects. This doesn't exclude that in similarly positioned countries, processing times might have similarly increased or decreased. Rather, these results suggest that similar reactions in terms of processing times might have been due to similar changes in the explanatory variables and to unobserved, common factors.

We also note that another possibility for this lack of results is the lack of statistical power, due to a moderate sample. For completeness, we show impulse-response graphs in Figure 3.A.1.

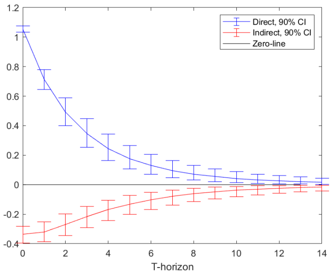
Table 3.A.1: SPDP Model, processing times, benchmark result summary

	Geographic proximity			Linguistic proximity		
	No factors	***With factors***		***No factors***	***With factors***	
	Overall	*Overall*	*High-recognition*	*Overall*	*Overall*	*High-recognition*
ρ	0.8715***	0.6424***	0.2446***	0.9224***	0.856***	0.2472***
	(0.0211)	(0.0299)	(0.0375)	(0.0219)	(0.0215)	(0.0377)
λ_1	0.021	-0.7352***	-0.0682	0.0063	-0.0117	-0.1333
	(0.0509)	(0.0855)	(0.0849)	(0.1008)	(0.1121)	(0.1071)
λ_2	-0.0552	0.2041*	0.2519**	-0.0467	-0.0795	-0.0372
	(0.0551)	(0.1076)	(0.1078)	(0.1183)	(0.1366)	(0.1603)
Obs	621	644	644	621	644	644
$\rho + \lambda_1 + \lambda_2$	[0.773, 0.903]	[-0.136, 0.363]	[0.165, 0.688]	[0.726, 1.031]	[0.522, 1.008]	[-0.271, 0.419]
$\lambda_1 + \lambda_2$	[-0.086, 0.02]	[-0.735, -0.336]	[-0.04, 0.41]	[-0.175, 0.081]	[-0.295, 0.121]	[-0.489, 0.126]
Factors	**X**	✓	✓	**X**	✓	✓
Nr factors	NA	ER:1; GR:5	ER:1; GR:1	NA	ER:1; GR:1	ER:1; GR:1
Controls: Economic	✓	✓	✓	✓	✓	✓
Controls: Political	✓	✓	✓	✓	✓	✓
Controls: Demographic	✓	✓	✓	✓	✓	✓

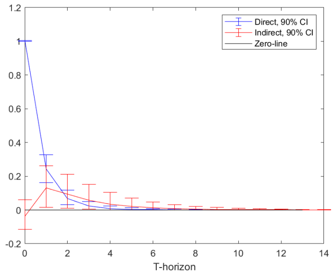
Notes: standard errors in parentheses. These results correspond to regression estimates for for our baseline model on processing times. Interaction matrices considered are based on geographic neighbors (column 1 to 3) and linguistic neighbors (column 4 to 6). Column 1 and column 4 show estimates for an SPDP model that doesn't include interactive effects. For these regressions, we apply the QML estimator of Lee and Yu, 2010b. Their bias-corretion transformation reduces the sample size (hence the lower N in these columns) and requires row-normalization. Interactive effects are included in column 2 to 3, and 5 to 6. Columns 3 and 6 zoom into processing speed for highly accepted origins, whilst for all other columns, overall patterns are considered. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Below these statistics, we report the number of estimated factors, following the growth ratio (GR) criterion. We also report the number of factors suggested by the Eigenvalue ratio (ER), for completeness. In these regressions, we control for the full set of economic, political and demographic covariates. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Figure 3.A.1: Processing times, impulse-response

Geographic proximity

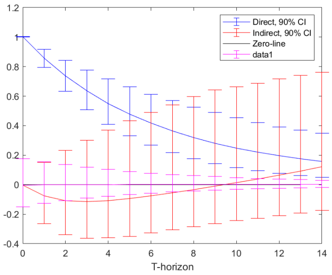


(a) Overall

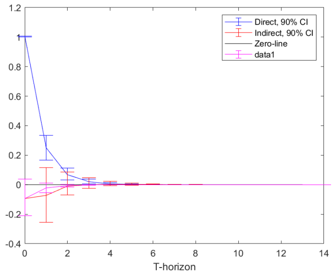


(b) High-recognition origins

Linguistic proximity



(c) Overall



(d) High-recognition origins

Notes: Impulse-response graphs on Bertoli et al., 2022's processing times. These graphs represent the impact over time from an exogenous shock in the rate of processing of a country, on the estimated processing times of the country itself (blue line), the average indirect effects onto other countries (red line) and, when an additional restriction allows, the indirect effects on the countries' first neighbors (magenta line). The top side of the graph represents effects based on geographic proximity, whilst results for linguistic proximity are shown on the bottom. On the left, results pertain to overall processing times, while on the right, we plot results for a subset of origins with high recognition rates. We report effects for an horizon of 15 periods, starting with the simultaneous results at t=0. 10% confidence intervals are reported around the point estimates.

3.B Additional tables

Table 3.B.1: Summary statistics

	Mean	Standard Deviation	N	Min	Max
Acceptance rates	0.457	0.218	644	0.000	0.987
Processing speed	0.976	0.914	644	0.046	11.000
Processing times	9.793	6.974	644	1.000	46.667
Gdp per capita, lagged (log)	1.918	0.650	644	0.493	3.214
Unemployment rate, lagged	8.156	4.151	644	2.100	26.300
Population, lagged (log)	9.069	1.469	644	6.036	11.327
Stocks of foreign population, lagged (log)	13.129	1.633	644	9.835	16.085
Displaced people	9.626	2.351	644	4.205	14.192
Total asylum applications	7.997	2.468	644	2.590	13.393
Displaced people, EU border	3.766	4.525	644	0.000	12.777
Populism, lagged	0.075	0.263	644	0.000	1.000
Social protection, lagged (log)	5.454	0.983	644	2.460	7.011

Notes: Summary statistics for the estimation sample.

Table 3.B.2: List of variables and sources

	Variable Description	Variable Source
Policy measures		
Acceptance rate	Percentage of first-instance decisions with a positive outcome -i.e. decisions granting refugee/subsidiary protection status, authorisation to stay for humanitarian reasons and temporary protection. The total number of decisions includes positive decisions plus rejected applicants. Computed following Bertoli et al., 2022.	Eurostat: First instance decisions on applications by citizenship, age and sex - quarterly data (rounded).
Processing speed	Number of total decisions over the number of first instance applications in the quarter.	Eurostat: First instance decisions on applications by citizenship, age and sex - quarterly data (rounded).
RHS measures		
Processing times	Given $a_{k(t-r;t)}$ = count of first-time asylum applications in receiving country k between month t-r-1 and month t-1 and given the stock of pending applications s_{kt-1} at the end of month t-1, the expected processing time equals the value of r s.t. $a_{k(t-r;t)} > s_{kt-1}$, and $a_{k(t-r-1;t)} < s_{kt-1}$. Following Bertoli et al., 2022, we exclude origins with $< 1\%$ frequency over all applications. We compute this index at monthly level and aggregate (averaged) at quarterly level.	Eurostat: Persons subject of asylum applications pending at the end of the month - monthly data.
RHS measures		
Total asylum applications	Log of total number of asylum applications.	UNHCR's Refugee Population Statistics Database.
Population	Log of population, quarterly frequency.	Eurostat: Employment and population - international data cooperation quarterly data.
Gdp per capita	Seasonally and calendar adjusted GDP at current prices, million euros, divided by population size	Eurostat: GDP and main components (output, expenditure and income) – quarterly data.
Unemployment rate	Number of unemployed persons as a percentage of the active population (labour force).	Eurostat: Unemployment by sex and age – quarterly data.
Presence of displaced population	Log of counts of presence of displaced people (UNHCR)	UNHCR's Refugee Population Statistics Database, compared with data from European Border and Coast Guard Agency (FRONTEX).
Crossings of migrants at external EU borders	Counts of presence of displaced people (UNHCR), weighted by the country's population, interacted with a dummy =1 if a country is part of external borders routes (routes-countries information are sourced by FRONTEX).	UNHCR's Refugee Population Statistics Database, compared with data from European Border and Coast Guard Agency (FRONTEX).
Populism	Dummy = 1 if for the year and country of reference there's a (right-wing or left-wing) populist party in power.	Funke et al., 2020. Retrieved at https://sites.google.com/view/manuel-funke/data.
Immigrant stocks (log)	Annual number of residents not having the citizenship of the reporting country (including stateless persons) on January 1st.	Eurostat: Population without the citizenship of the reporting country.
DE, post September 2015	Dummy = 1 for Germany, interacted with the second half of 2015.	Own computation.
Social-protection benefits	Social-protection benefits expenditures, benefits expenditures, purchasing power standard (PPS) per inhabitant.	Eurostat: Social protection (spr) expenditure - Tables by benefits and currency - yearly data.

Notes: Variables' description and sources for the estimation sample.

Table 3.B.3: SPDP Model acceptance rate, no common factors

	Static models			Dynamic spatial models	
	FE	*SAR*	*SDM*	*Geographic proximity*	*Language proximity*
Regressors	FE	Static SAR	Static SDM	SPDP	SPDP
Gdp per capita$_{(t-1)}$	.177	.134	-.05	0.1029	0.0445
	(.291)	(.125)	(.14)	(0.1225)	(0.1124)
Unemployment$_{(t-1)}$	-.006	-.007	-.007	0.0077	-0.0082
	(.017)	(.006)	(.007)	(0.0076)	(0.0068)
Population$_{(t-1)}$	2.615*	2.683***	1.54**	1.8715***	1.5369***
	(1.452)	(.483)	(.61)	(0.5953)	(0.5733)
Stocks of immigrants$_{(t-1)}$	-.38*	-.376***	-.442***	-0.1264**	-0.1934**
	(.21)	(.067)	(.089)	(0.0634)	(0.0816)
Asylum presence	.185***	.184***	.22***	0.0637*	0.0753**
	(.051)	(.037)	(.04)	(0.0356)	(0.0363)
Tot. applications	-.027	-.023	-.038**	-0.0055	-0.0026
	(.025)	(.016)	(.017)	(0.0151)	(0.0151)
Asylum, external borders	-.095	-.099***	-.161***	-0.0663*	-0.0292
	(.058)	(.034)	(.039)	(0.0364)	(0.0394)
Populism$_{(t-1)}$	.045	.039	.043	0.0256	-0.0554
	(.104)	(.056)	(.059)	(0.0495)	(0.0583)
Social protetion$_{(t-1)}$	.156*	.164***	.132***	0.1236**	0.0498
	(.081)	(.043)	(.047)	(0.0513)	(0.0455)
DE, Post Nov 2015	.029	.046	.081	0.0702	0.0441
	(.039)	(.159)	(.153)	(0.1347)	(0.1373)
W: Gdp per capita$_{(t-1)}$			-2.292***	-0.1737	-0.6575
			(.14)	(0.2001)	(0.4719)
W: Unemployment$_{(t-1)}$			-.111***	-0.0439***	-0.0776**
			(.007)	(0.0137)	(0.0327)
W: Population$_{(t-1)}$			1.328	-0.0294	3.1973
			(.61)	(1.2806)	(2.4942)
W: Stocks of immigrants$_{(t-1)}$			.28	-0.1455	-0.3267
			(.089)	(0.1436)	(0.4173)
W: Asylum presence			.105	0.0179	0.3413***
			(.04)	(0.0704)	(0.1059)
W: Tot. applications			.012	0.0002	-0.1683***
			(.017)	(0.0249)	(0.0527)
W: Asylum, external borders			-.623***	-0.1149	-0.0016
			(.039)	(0.0706)	(0.1231)
W: Populism$_{(t-1)}$			-.479**	0.0072	-0.4136*
			(.059)	(0.0743)	(0.2486)
W: Social protetion$_{(t-1)}$			-.137	-0.0296	0.2231
			(.047)	(0.0962)	(0.1989)
W: DE, Post Nov 2015			1.953*	0.3212	0.2838
			(.153)	(0.379)	(0.6257)
ρ				0.5983***	0.6221***
				(0.0355)	(0.035)
$\lambda 1$			-.297***	0.0009	0.0023
			(.09)	(0.049)	(0.0976)
$\lambda 2$		-.082*		0.0095	-0.2109*
		(.042)		(0.0656)	(0.1225)
N	644	644	644	621	621
Stability				10% CI: 0.495 - 0.733	10% CI: 0.209 - 0.62
	Pesaran 2015			$\lambda 1 + \lambda 2$	$\lambda 1 + \lambda 2$
	p-val:.001			10% CI: -0.085 - 0.119	10% CI: -0.394 - -0.027

Notes: standard errors in parentheses. These results correspond to regression estimates on the levels of acceptance rates, for a panel of 23 European countries with quarterly data from 2013 to 2019. Column 1 presents results from a within estimator, without spatial parameters. At the bottom of the table, we report the p-value of Pesaran, 2015's test to detect strong or weak cross-sectional dependence in the panel. columns 2 and 3 present results based on a static spatial panel and belong to a SAR and SDM specification, respectively, based on geographic distance matrices. Variable names prefixed by W indicate spatial lags of the explanatory variables. Column 4 to 6 present coefficients from the SPDP model on the outcome levels. Interaction matrices considered are based on geographic neighbors and linguistic neighbors. At the bottom of SPDP model results, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table 3.B.4: SPDP Model, acceptance rate, common factors

	Geographic proximity		Linguistic proximity	
	Overall	*High-recognition*	*Overall*	*High-recognition*
Regressors	SPDP	SPDP	SPDP	SPDP
Gdp per capita$_{(t-1)}$	0.3668***	-0.1108*	-0.0799	0.0526
	(0.0856)	(0.0622)	(0.0664)	(0.0444)
Unemployment$_{(t-1)}$	0.0154***	0.0052	-0.0126***	-0.0089***
	(0.0059)	(0.0056)	(0.0048)	(0.0034)
Population$_{(t-1)}$	0.1697***	-0.0283	-0.0573*	0.1215***
	(0.0483)	(0.03)	(0.0337)	(0.0312)
Stocks of immigrants$_{(t-1)}$	-0.199***	-0.0151	0.0416*	-0.0926***
	(0.0433)	(0.0222)	(0.0236)	(0.0257)
Asylum presence	0.0326	0.023	0.037**	0.0552***
	(0.0227)	(0.0181)	(0.0182)	(0.0124)
Tot. applications	0.0042	0.0527***	-0.0131	-0.0037
	(0.0121)	(0.0061)	(0.0113)	(0.0035)
Asylum, external borders	-0.0032	0.0095*	0.0008	-0.0094
	(0.0079)	(0.0056)	(0.0051)	(0.009)
Populism$_{(t-1)}$	0.0284	0.1573***	-0.0863**	0.0151
	(0.0438)	(0.0567)	(0.0423)	(0.0276)
Social protetion$_{(t-1)}$	0.01	0.1058***	0.0033	0.1079***
	(0.0316)	(0.0344)	(0.0206)	(0.0207)
DE, Post Nov 2015	0.0329	0.0394	0.0242	-0.5078***
	(0.1188)	(0.1445)	(0.1242)	(0.1723)
W: Gdp per capita$_{(t-1)}$	0.0237	-1.0847***	-1.2984***	-0.865***
	(0.3607)	(0.2497)	(0.3744)	(0.293)
W: Unemployment$_{(t-1)}$	-0.0203	-0.0893***	-0.0336	-0.1027***
	(0.0193)	(0.0176)	(0.0232)	(0.0261)
W: Population$_{(t-1)}$	0.6096***	0.0239	-0.5918**	0.3502
	(0.2237)	(0.1055)	(0.2477)	(0.2486)
W: Stocks of immigrants$_{(t-1)}$	-0.6403***	-0.0637	0.4928**	-0.0337
	(0.182)	(0.0722)	(0.2013)	(0.187)
W: Asylum presence	0.0926	0.0448	0.2153**	0.0856
	(0.0773)	(0.0661)	(0.0865)	(0.0769)
W: Tot. applications	0.0563	-0.0277	-0.0479	-0.0649***
	(0.0384)	(0.0187)	(0.045)	(0.0192)
W: Asylum, external borders	-0.0796*	0.1076***	-0.023	-0.0422
	(0.0483)	(0.0301)	(0.0386)	(0.0602)
W: Populism$_{(t-1)}$	0.3039*	0.6722**	-0.1252	-0.1039
	(0.1691)	(0.2686)	(0.2427)	(0.1813)
W: Social protetion$_{(t-1)}$	0.3401**	0.5319***	0.0306	-0.0259
	(0.1353)	(0.1152)	(0.1152)	(0.1643)
W: DE, Post Nov 2015	0.1674	-0.0235	0.1385	-6.4747***
	(0.3417)	(0.3991)	(0.4538)	(1.3602)
ρ	0.6152***	0.2314***	0.6377***	0.1738***
	(0.032)	(0.0365)	(0.0338)	(0.0389)
$\lambda 1$	-0.3906***	-0.1652*	-0.3179**	-0.5211***
	(0.0917)	(0.0866)	(0.1242)	(0.1339)
$\lambda 2$	0.2977**	0.3481***	0.3191**	0.4934***
	(0.1207)	(0.1109)	(0.1607)	(0.1141)
N	644	644	644	644
Stability	90% CI: 0.287 - 0.777	90% CI: 0.151 - 0.694	90% CI: 0.349 - 0.934	90% CI: -0.176 - 0.496
	$\lambda 1 + \lambda 2$	$\lambda 1 + \lambda 2$	$\lambda 1 + \lambda 2$	$\lambda 1 + \lambda 2$
	90% CI: -0.3 - 0.117	90% CI: -0.043 - 0.425	90% CI: -0.263 - 0.253	90% CI: -0.292 - 0.259

Notes: standard errors in parentheses. These results correspond to regression estimates from an SPDP model on acceptance rates, with interactive effects. Interaction matrices considered are based on geographic neighbors (column 1 and 2), and linguistic neighbors (column 3 and 4). Column 1 and 3 pertain to results on overall acceptance, whilst in columns 2 and 4 we disaggregate the overall patterns and focus on high-recognition origins. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Stars correspond to the following p-values: * p < .10, ** p < .05, *** p < .001.

Table 3.B.5: SPDP Model processing speed, no common factors

	Static models			Dynamic spatial models	
	FE	*SAR*	*SDM*	*Geographic proximity*	*Language proximity*
Regressors	FE	Static SAR	Static SDM	SPDP	SPDP
Gdp per capita$_{(t-1)}$	-1.384	-1.25**	-1.513**	-0.0099	-0.6524
	(.969)	(.61)	(.704)	(0.6616)	(0.6285)
Unemployment$_{(t-1)}$	.046	.058*	.062	0.0675*	0.003
	(.045)	(.033)	(.037)	(0.0402)	(0.0377)
Population$_{(t-1)}$	-1.691	-2.742	-3.602	-1.0103	-0.8315
	(2.622)	(2.399)	(3.063)	(3.0977)	(3.1176)
Stocks of immigrants$_{(t-1)}$	-.833	-.786**	-.483	-0.6913**	-0.7533*
	(.609)	(.335)	(.45)	(0.3294)	(0.4454)
Asylum presence	-.079	-.077	-.418**	-0.2474	-0.174
	(.406)	(.187)	(.204)	(0.1881)	(0.1983)
Tot. applications	.262	.253***	.337***	0.2866***	0.315***
	(.207)	(.08)	(.087)	(0.0815)	(0.0843)
Asylum, external borders	-.004	.021	.083	0.0166	-0.0005
	(.313)	(.172)	(.196)	(0.1897)	(0.2172)
Populism$_{(t-1)}$	.946	.941***	1.005***	0.5965**	0.4263
	(.573)	(.277)	(.3)	(0.2678)	(0.325)
Social protetion$_{(t-1)}$	.412	.387*	.417*	0.1791	0.3634
	(.287)	(.212)	(.236)	(0.2672)	(0.2509)
DE, Post Nov 2015	-.357**	-.32	-.378	-0.3025	-0.3589
	(.135)	(.787)	(.77)	(0.7209)	(0.7653)
W: Gdp per capita$_{(t-1)}$			-3.945	-1.5399	-2.3632
			(.704)	(1.0752)	(2.5741)
W: Unemployment$_{(t-1)}$			.096	-0.0587	-0.251
			(.037)	(0.0705)	(0.1784)
W: Population$_{(t-1)}$			-26.011***	-0.9451	13.3434
			(3.063)	(6.8504)	(13.8364)
W: Stocks of immigrants$_{(t-1)}$			3.714***	-0.2463	-0.4826
			(.45)	(0.766)	(2.2929)
W: Asylum presence			-.783	-0.3132	0.3908
			(.204)	(0.3766)	(0.5711)
W: Tot. applications			.194	0.1983	0.1789
			(.087)	(0.1395)	(0.2957)
W: Asylum, external borders			1.515	0.0128	-0.7369
			(.196)	(0.3708)	(0.6811)
W: Populism$_{(t-1)}$			.664	-0.8247**	-1.6874
			(.3)	(0.4034)	(1.3843)
W: Social protetion$_{(t-1)}$			-1.24	0.4452	0.6012
			(.236)	(0.5199)	(1.1141)
W: DE, Post Nov 2015			2.523	-1.0974	-5.1041
			(.77)	(2.0266)	(3.5263)
ρ				0.3595***	0.4267***
				(0.0395)	(0.0378)
$\lambda 1$			-.366***	0.2436***	0.2353
			(.097)	(0.0941)	(0.1477)
$\lambda 2$		-.141***		0.0709	0.1614
		(.043)		(0.067)	(0.1391)
N	644	644	644	621	621
Stability				10% CI: 0.57 - 0.789	10% CI: 0.602 - 1.032
	Pesaran 2015			$\lambda 1 + \lambda 2$	$\lambda 1 + \lambda 2$
	p-val:.283			10% CI: 0.208 - 0.436	10% CI: 0.184 - 0.607

Notes: standard errors in parentheses. These results correspond to regression estimates on processing speed, for a panel of 23 European countries with quarterly data from 2013 to 2019. Column 1 presents results from a within estimator, without spatial parameters. At the bottom of the table, we report the p-value of Pesaran, 2015's test to detect strong or weak cross-sectional dependence in the panel. columns 2 and 3 present results based on a static spatial panel and belong to a SAR and SDM specification, respectively, based on geographic distance matrices. Variable names prefixed by W indicate spatial lags of the explanatory variables. Column 4 to 6 present coefficients from the SPDP model on the outcome levels. Interaction matrices considered are based on geographic neighbors and linguistic neighbors. At the bottom of SPDP model results, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Stars correspond to the following p-values: * p $<$ .10, ** p $<$ .05, *** p $<$ .001.

Table 3.B.6: SPDP Model, processing speed, common factors

	Geographic proximity		Linguistic proximity	
	Overall	*High-recognition*	*Overall*	*High-recognition*
Regressors	SPDP	SPDP	SPDP	SPDP
Gdp per capita$_{(t-1)}$	0.176	0.5331	0.976***	0.2264
	(0.1397)	(0.647)	(0.3601)	(0.7815)
Unemployment$_{(t-1)}$	0.0004	0.0276	-0.0179	-0.0393
	(0.008)	(0.0618)	(0.0156)	(0.0522)
Population$_{(t-1)}$	-0.0455	0.2601	0.8084***	-0.0643
	(0.042)	(0.2769)	(0.2633)	(0.3933)
Stocks of immigrants$_{(t-1)}$	-0.0099	-0.52***	-0.5239***	-0.3329
	(0.04)	(0.1931)	(0.1968)	(0.2601)
Asylum presence	0.0315	0.4797**	-0.2304***	0.5289**
	(0.0494)	(0.2096)	(0.0877)	(0.233)
Tot. applications	-0.0066	-0.4034***	0.021	-0.5818***
	(0.0341)	(0.1116)	(0.0474)	(0.1132)
Asylum, external borders	0.0338***	-0.0153	-0.0779	0.1667***
	(0.0083)	(0.0348)	(0.0666)	(0.0618)
Populism$_{(t-1)}$	0.2935***	-0.4281	0.3139*	-0.6678
	(0.0901)	(0.8247)	(0.1662)	(0.8306)
Social protetion$_{(t-1)}$	0.0285	0.3919	-0.0655	0.5797**
	(0.0438)	(0.3285)	(0.1158)	(0.2944)
DE, Post Nov 2015	-0.2865	0.5834	-0.2892	0.4353
	(0.3773)	(2.7291)	(0.3938)	(2.7296)
W: Gdp per capita$_{(t-1)}$	1.7371***	-3.9415*	2.3718	-3.0191
	(0.5096)	(2.2476)	(2.0953)	(3.8701)
W: Unemployment$_{(t-1)}$	0.0778**	0.0511	-0.1358	-0.126
	(0.0382)	(0.187)	(0.0938)	(0.3058)
W: Population$_{(t-1)}$	0.4107**	-3.2806***	0.2152	-3.9635
	(0.1951)	(1.137)	(1.3141)	(2.7672)
W: Stocks of immigrants$_{(t-1)}$	-0.5361***	0.8468	-0.0886	0.6125
	(0.1976)	(0.7079)	(1.0718)	(2.1179)
W: Asylum presence	-0.2975*	2.1257**	-0.0212	1.3307
	(0.1537)	(0.9258)	(0.349)	(1.2438)
W: Tot. applications	0.2876**	-0.7629**	-0.2623	-0.0933
	(0.1226)	(0.3168)	(0.2329)	(0.4056)
W: Asylum, external borders	0.1268**	0.3207*	0.5829**	1.3578***
	(0.0501)	(0.1785)	(0.2659)	(0.4584)
W: Populism$_{(t-1)}$	0.3718	4.6322	0.5347	-1.9358
	(0.3529)	(3.0981)	(0.9524)	(3.6476)
W: Social protetion$_{(t-1)}$	-0.118	1.6352	-0.1549	3.4969**
	(0.2052)	(1.1078)	(0.5771)	(1.5972)
W: DE, Post Nov 2015	-3.724***	-3.6731	-4.5775**	-7.2923
	(1.4367)	(7.6095)	(1.8071)	(8.5877)
ρ	0.629***	0.3636***	0.2095***	0.3813***
	(0.0316)	(0.0402)	(0.0427)	(0.0394)
$\lambda1$	-0.693***	0.0413	-0.6233***	0.1319
	(0.0874)	(0.0804)	(0.137)	(0.0895)
$\lambda2$	0.7331***	-0.0502	-0.0297	-0.0246
	(0.1011)	(0.0616)	(0.1072)	(0.066)
N	644	644	644	644
Stability	90% CI: 0.422 - 0.905	90% CI: 0.153 - 0.553	90% CI: -0.778 - -0.095	90% CI: 0.278 - 0.698
	$\lambda1 + \lambda2$	$\lambda1 + \lambda2$	$\lambda1 + \lambda2$	$\lambda1 + \lambda2$
	90% CI: -0.149 - 0.217	90% CI: -0.164 - 0.136	90% CI: -0.944 - -0.345	90% CI: -0.057 - 0.262

Notes: standard errors in parentheses. These results correspond to regression estimates from an SPDP model on processing speed, with interactive effects. Interaction matrices considered are based on geographic neighbors (column 1 and 2), and linguistic neighbors (column 3 and 4). Column 1 and 3 pertain to results on overall processing speed, whilst in columns 2 and 4 we disaggregate the overall patterns and focus on high-recognition origins. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Stars correspond to the following p-values: * p < .10, ** p < .05, *** p < .001.

Table 3.B.7: SPDP Model processing times, no common factors

	Static models			Dynamic spatial models	
	FE	*SAR*	*SDM*	*Geographic proximity*	*Language proximity*
Regressors	FE	Static SAR	Static SDM	SPDP	SPDP
Gdp per capita$_{(t-1)}$	-30.834***	-29.163***	-30.012***	-3.3873*	-0.9203
	(10.286)	(2.673)	(3.058)	(1.7788)	(1.7293)
Unemployment$_{(t-1)}$	.04	.095	.476***	0.2148**	0.1799**
	(.274)	(.145)	(.162)	(0.0966)	(0.0885)
Population$_{(t-1)}$	-66.201*	-72.103***	-84.33***	-22.3627***	-13.3313*
	(35.465)	(10.415)	(13.128)	(7.6845)	(7.4759)
Stocks of immigrants$_{(t-1)}$	14.61***	14.787***	9.285***	1.1311	0.0254
	(3.958)	(1.453)	(1.938)	(0.8603)	(1.1366)
Asylum presence	-3.086	-3.037***	-4.619***	-1.1149**	-0.3342
	(2.045)	(.812)	(.876)	(0.4551)	(0.4648)
Tot. applications	1.557***	1.39***	2.291***	1.1187***	1.2714***
	(.483)	(.351)	(.376)	(0.1961)	(0.1966)
Asylum, external borders	4.27**	4.39***	5.614***	0.075	-0.8011
	(1.841)	(.746)	(.845)	(0.4667)	(0.5328)
Populism$_{(t-1)}$	1.447	.981	-1.826	0.806	0.5698
	(1.766)	(1.21)	(1.293)	(0.639)	(0.7557)
Social protetion$_{(t-1)}$	2.396	1.931**	1.224	-0.8689	-0.3267
	(1.845)	(.926)	(1.014)	(0.6441)	(0.5927)
DE, Post Nov 2015	-1.868*	-1.082	-1.503	-1.8043	-1.0938
	(.942)	(3.422)	(3.304)	(1.7291)	(1.7788)
W: Gdp per capita$_{(t-1)}$			54.96***	-6.7369**	3.3722
			(3.058)	(2.7714)	(7.2736)
W: Unemployment$_{(t-1)}$			2.951***	0.2076	0.6707
			(.162)	(0.1722)	(0.4271)
W: Population$_{(t-1)}$			-129.73***	-34.3903**	-86.9648***
			(13.128)	(16.7598)	(32.9387)
W: Stocks of immigrants$_{(t-1)}$			-1.766	-2.8535	-6.6324
			(1.938)	(1.8913)	(5.9618)
W: Asylum presence			5.844*	1.2111	0.4362
			(.876)	(0.9005)	(1.4236)
W: Tot. applications			1.495	0.0346	-0.4809
			(.376)	(0.3248)	(0.6909)
W: Asylum, external borders			.211	-1.1826	-4.8287***
			(.845)	(0.9042)	(1.8432)
W: Populism$_{(t-1)}$			-2.646	-0.3974	-3.7816
			(1.293)	(0.9586)	(3.2397)
W: Social protetion$_{(t-1)}$			-19.062***	1.4702	-1.5646
			(1.014)	(1.2341)	(2.5901)
W: DE, Post Nov 2015			33.131	-4.0639	-3.6242
			(3.304)	(4.8635)	(8.1073)
ρ				0.8715***	0.9224***
				(0.0211)	(0.0219)
$\lambda 1$			-.276***	0.021	0.0063
			(.092)	(0.0509)	(0.1008)
$\lambda 2$		-.162***		-0.0552	-0.0467
		(.04)		(0.0551)	(0.1183)
N	644	644	644	621	621
Stability				10% CI: 0.773 - 0.903	10% CI: 0.726 - 1.031
	Pesaran 2015			$\lambda 1 + \lambda 2$	$\lambda 1 + \lambda 2$
	p-val:.001			10% CI: -0.086 - 0.02	10% CI: -0.175 - 0.081

Notes: standard errors in parentheses. These results correspond to regression estimates on processing times, for a panel of 23 European countries with quarterly data from 2013 to 2019. Column 1 presents results from a within estimator, without spatial parameters. At the bottom of the table, we report the p-value of Pesaran, 2015's test to detect strong or weak cross-sectional dependence in the panel. columns 2 and 3 present results based on a static spatial panel and belong to a SAR and SDM specification, respectively, based on geographic distance matrices. Variable names prefixed by W indicate spatial lags of the explanatory variables. Column 4 to 6 present coefficients from the SPDP model on the outcome levels. Interaction matrices considered are based on geographic neighbors and linguistic neighbors. At the bottom of SPDP model results, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table 3.B.8: SPDP Model, processing times, common factors

	Geographic proximity		Linguistic proximity	
	Overall	*High-recognition*	*Overall*	*High-recognition*
Regressors	SPDP	SPDP	SPDP	SPDP
Gdp per capita$_{(t-1)}$	0.9581	4.1298**	-3.104*	8.0537***
	(1.8995)	(1.6804)	(1.6447)	(2.1329)
Unemployment$_{(t-1)}$	0.8555***	-0.0806	0.2384***	-0.0852
	(0.1083)	(0.1552)	(0.0775)	(0.1288)
Population$_{(t-1)}$	-4.6145***	-0.0804	-6.2165	0.1928
	(1.5953)	(0.6828)	(3.7932)	(0.9558)
Stocks of immigrants$_{(t-1)}$	3.0188***	0.8085	-0.7632	1.3109*
	(1.0256)	(0.5354)	(0.8724)	(0.6689)
Asylum presence	-2.0399***	-2.3339***	0.0333	-3.5639***
	(0.4964)	(0.4842)	(0.4297)	(0.5616)
Tot. applications	1.8048***	1.9142***	1.2767***	2.1212***
	(0.1908)	(0.2231)	(0.1868)	(0.233)
Asylum, external borders	1.2173**	0.0394	-0.9058	0.355**
	(0.4882)	(0.0891)	(0.552)	(0.1682)
Populism$_{(t-1)}$	-0.522	9.153***	0.7019	7.5008***
	(0.7054)	(1.6744)	(0.7218)	(1.4871)
Social protetion$_{(t-1)}$	0.3859	0.0069	-0.0931	-1.1373
	(0.7342)	(0.7795)	(0.4939)	(0.6969)
DE, Post Nov 2015	-0.2215	-1.2093	-1.3234	-1.9703
	(1.192)	(5.612)	(1.7112)	(5.7384)
W: Gdp per capita$_{(t-1)}$	40.0415***	0.7435	-11.0405	1.409
	(8.9119)	(5.908)	(10.6399)	(10.2425)
W: Unemployment$_{(t-1)}$	0.8522**	-0.6924	-0.4825	0.195
	(0.3356)	(0.4889)	(0.4736)	(0.6624)
W: Population$_{(t-1)}$	-16.0176**	1.4687	5.6661	-15.3574**
	(6.2812)	(2.9201)	(8.1948)	(6.6918)
W: Stocks of immigrants$_{(t-1)}$	8.6043*	-1.2694	-4.1759	12.5153**
	(4.5568)	(1.8937)	(6.8371)	(5.2647)
W: Asylum presence	-8.0798***	-2.3186	1.6964	-2.4955
	(1.5343)	(2.0877)	(2.1356)	(2.7552)
W: Tot. applications	2.4004***	-0.8091	-1.5653*	-1.2507
	(0.7943)	(0.7319)	(0.8408)	(0.9607)
W: Asylum, external borders	15.8405***	0.3195	-4.6361	2.2344*
	(2.7466)	(0.4511)	(3.2905)	(1.2095)
W: Populism$_{(t-1)}$	-1.8166	4.9295	-5.9454	2.5641
	(3.5295)	(6.5403)	(4.3094)	(7.965)
W: Social protetion$_{(t-1)}$	5.1805**	5.4144*	5.9924**	-0.6319
	(2.5203)	(2.9581)	(3.0109)	(3.5702)
W: DE, Post Nov 2015	-10.7256*	-1.5247	-7.1687	-6.1931
	(6.1166)	(15.8756)	(7.2903)	(18.137)
ρ	0.6424***	0.2446***	0.856***	0.2472***
	(0.0299)	(0.0375)	(0.0215)	(0.0377)
$\lambda1$	-0.7352***	-0.0682	-0.0117	-0.1333
	(0.0855)	(0.0849)	(0.1121)	(0.1071)
$\lambda2$	0.2041*	0.2519**	-0.0795	-0.0372
	(0.1076)	(0.1078)	(0.1366)	(0.1603)
N	644	644	644	644
Stability	90% CI: -0.136 - 0.363	90% CI: 0.165 - 0.688	90% CI: 0.522 - 1.008	90% CI: -0.271 - 0.419
	$\lambda1 + \lambda2$	$\lambda1 + \lambda2$	$\lambda1 + \lambda2$	$\lambda1 + \lambda2$
	90% CI: -0.735 - -0.336	90% CI: -0.04 - 0.41	90% CI: -0.295 - 0.121	90% CI: -0.489 - 0.126

Notes: standard errors in parentheses. These results correspond to regression estimates from our baseline SPDP model with interactive fixed effects on processing times. Interaction matrices considered are based on geographic neighbors, linguistic neighbors. At the bottom, we report a 10% confidence interval from testing for the model's stability (P. Elhorst et al., 2013), as well as a test for the significance of the summed spatial parameters. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

3.B.1 Short-term and long-term direct and indirect effects

Table 3.B.9: Direct, indirect effects on acceptance rates

	Geographic proximity:							
Variables:	ST Direct	ST Indirect	LT Direct	LT Indirect	ST Direct	ST Indirect	LT Direct	LT Indirect
Gdp per capita$_{(t-1)}$	0.3733***	-0.0596	1.0136	0.4071	-0.0906	-0.6154***	-0.1068	-0.779***
	(0.0897)	(0.1803)	(0.6382)	(5.2885)	(0.0688)	(0.1447)	(0.102)	(0.2073)
Unemployment$_{(t-1)}$	0.0167	-0.0129	0.0447	-0.0511	0.0076	-0.0504***	0.0121	-0.0676***
	(0.0308)	(0.0148)	(0.0967)	(0.2602)	(0.0306)	(0.0177)	(0.0423)	(0.024)
Population$_{(t-1)}$	0.1495***	0.2828***	0.5345	1.5565	-0.0283	0.015	-0.036	0.0174
	(0.0575)	(0.1176)	(0.7326)	(6.428)	(0.0443)	(0.0631)	(0.0573)	(0.0808)
Stocks of immigrants$_{(t-1)}$	-0.178***	-0.2882***	-0.6127	-1.6951	-0.0126	-0.0316	-0.0149	-0.0433
	(0.05)	(0.0912)	(0.8591)	(7.6827)	(0.0376)	(0.0436)	(0.0499)	(0.0565)
Asylum presence	0.0342	-0.0075	0.0934	-0.0058	0.0233	0.0047	0.0315	0.0014
	(0.038)	(0.0123)	(0.1151)	(0.1811)	(0.0361)	(0.016)	(0.0484)	(0.0182)
Tot. applications	0.0028	0.0287	0.0231	0.1138	0.0544*	-0.0194	0.0732*	-0.0305
	(0.0328)	(0.0219)	(0.1017)	(0.4582)	(0.0307)	(0.0189)	(0.044)	(0.0214)
Asylum, external borders	0.0006	-0.0405	-0.0102	-0.1983	0.0086	0.0619***	0.0114	0.0746***
	(0.0308)	(0.026)	(0.1169)	(0.6516)	(0.0311)	(0.0235)	(0.0396)	(0.0283)
Populism$_{(t-1)}$	0.0174	0.1467*	0.1141	0.6799	0.152**	0.3771***	0.1945**	0.4678**
	(0.0532)	(0.0865)	(0.3621)	(3.0317)	(0.0661)	(0.1524)	(0.0859)	(0.2035)
Social protetion$_{(t-1)}$	-0.0004	0.1701***	0.0775	0.7823	0.0966**	0.2977***	0.1232*	0.3697***
	(0.0458)	(0.0696)	(0.3011)	(2.5813)	(0.0489)	(0.0701)	(0.0637)	(0.1016)
DE, Post Nov 2015	0.022	0.0782	0.0932	0.3314	0.0421	-0.0215	0.0571	-0.0316
	(0.1232)	(0.1735)	(0.3749)	(1.6099)	(0.1555)	(0.2283)	(0.2064)	(0.2883)
	Linguistic proximity:							
Variables:	ST Direct	ST Indirect	LT Direct	LT Indirect	ST Direct	ST Indirect	LT Direct	LT Indirect
Gdp per capita$_{(t-1)}$	-0.0545	-0.8611***	-0.2739	-4.0569	0.0817	-0.524***	0.0646	-0.9155***
	(0.0703)	(0.2596)	(1.5809)	(26.0942)	(0.0537)	(0.1788)	(0.0786)	(0.3682)
Unemployment$_{(t-1)}$	-0.0125	-0.02	-0.0297	-0.1067	-0.0033	-0.0566***	-0.0068	-0.1113**
	(0.032)	(0.0217)	(0.1039)	(0.6834)	(0.0326)	(0.018)	(0.0416)	(0.0565)
Population$_{(t-1)}$	-0.0457	-0.3847***	-0.1807	-1.8721	0.113***	0.173	0.1528***	0.3887
	(0.0437)	(0.165)	(0.8202)	(13.5071)	(0.0435)	(0.1455)	(0.0616)	(0.3117)
Stocks of immigrants$_{(t-1)}$	0.0308	0.3222***	0.1447	1.5369	-0.0901**	0.007	-0.1089**	-0.0506
	(0.0381)	(0.1359)	(0.6818)	(11.2394)	(0.0389)	(0.1082)	(0.0481)	(0.2179)
Asylum presence	0.037	-0.0065	0.1133	0.0416	0.0596*	-0.0208	0.0727	-0.0086
	(0.0362)	(0.0176)	(0.1384)	(1.2156)	(0.0351)	(0.014)	(0.0465)	(0.0377)
Tot. applications	-0.0129	-0.0306	-0.0308	-0.1427	0.0004	-0.0362***	-0.0008	-0.072
	(0.0339)	(0.0338)	(0.1061)	(0.5148)	(0.0327)	(0.0148)	(0.0415)	(0.049)
Asylum, external borders	0.0005	-0.0146	0.0072	-0.0813	-0.0056	-0.0203	-0.0072	-0.0486
	(0.032)	(0.0286)	(0.1094)	(0.7788)	(0.0334)	(0.0362)	(0.0425)	(0.0832)
Populism$_{(t-1)}$	-0.0867*	-0.0697	-0.2345	-0.2442	0.0196	-0.0716	0.0208	-0.1186
	(0.0505)	(0.1607)	(0.2293)	(2.9777)	(0.0414)	(0.1027)	(0.0549)	(0.2014)
Social protetion$_{(t-1)}$	0.0013	0.0245	0.0134	0.0808	0.1128***	-0.0427	0.1358***	-0.0219
	(0.0394)	(0.0794)	(0.1418)	(1.3177)	(0.0373)	(0.0938)	(0.0532)	(0.1835)
DE, Post Nov 2015	0.0256	0.0875	0.0805	0.1981	-0.3063**	-3.6927***	-0.6395***	-6.9994***
	(0.1308)	(0.3166)	(0.4834)	(5.3094)	(0.1471)	(0.828)	(0.2657)	(2.1311)

Notes: standard errors in parentheses. This table presents estimates of short term and long term direct and indirect effects of each explanatory variable on acceptance rates, as resulting from our baseline SPDP model with interactive fixed effects. For comparison, its related coefficient table is table 3.5.1. In the three subsections, from left to right, interaction matrices considered are based on geographic neighbors, linguistic neighbors. To compute these values, we use formulas proposed in Belotti et al., 2013, while uncertainty measures are developed based on the procedure suggested in J. LeSage and Pace, 2009 and P. Elhorst et al., 2013. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

Table 3.B.10: Direct, indirect effects on processing speed

	Geographic proximity:							
	Overall				*High-recognition*			
Variables:	ST Direct	ST Indirect	LT Direct	LT Indirect	ST Direct	ST Indirect	LT Direct	LT Indirect
Gdp per capita$_{(t-1)}$	0.0631	0.753***	0.4012	2.8097***	0.5142	-2.5865*	0.8247	-4.0749*
	(0.1259)	(0.2027)	(0.4326)	(0.8996)	(0.6758)	(1.5179)	(1.0779)	(2.4084)
Unemployment$_{(t-1)}$	-0.0053	0.0361**	0.0034	0.1112	0.0284	0.0354	0.0464	0.0495
	(0.033)	(0.0179)	(0.09)	(0.0835)	(0.07)	(0.1216)	(0.1123)	(0.1907)
Population$_{(t-1)}$	-0.0771	0.2107***	-0.1419	0.6839**	0.2515	-2.1448***	0.4103	-3.3625***
	(0.0551)	(0.0881)	(0.1493)	(0.33)	(0.2843)	(0.7452)	(0.4722)	(1.2003)
Stocks of immigrants$_{(t-1)}$	0.0265	-0.2463***	0.0051	-0.8974***	-0.521***	0.5464	-0.8245***	0.8536
	(0.0454)	(0.0814)	(0.1904)	(0.3611)	(0.2)	(0.4621)	(0.3046)	(0.7309)
Asylum presence	0.0324	0.0056	0.0956	0.0383	0.4793**	0.004	0.7614**	-0.0062
	(0.0592)	(0.0177)	(0.1655)	(0.0647)	(0.2127)	(0.0476)	(0.3507)	(0.0763)
Tot. applications	-0.0278	0.1357***	-0.0287	0.4536**	-0.4053***	-0.5058***	-0.6382***	-0.792**
	(0.045)	(0.0546)	(0.117)	(0.222)	(0.1159)	(0.1927)	(0.1867)	(0.3498)
Asylum, external borders	0.0267	0.0478**	0.0944	0.1872*	-0.0149	0.2125*	-0.0227	0.3278*
	(0.0326)	(0.0218)	(0.0944)	(0.0989)	(0.0486)	(0.1195)	(0.0725)	(0.1887)
Populism$_{(t-1)}$	0.2834***	0.0721	0.8078***	0.535	-0.4062	2.9847	-0.6613	4.678
	(0.0892)	(0.1557)	(0.2905)	(0.6741)	(0.8209)	(2.0562)	(1.3195)	(3.243)
Social protetion$_{(t-1)}$	0.0389	-0.0672	0.0959	-0.2157	0.4022	1.0879	0.631	1.6934
	(0.0508)	(0.0836)	(0.1666)	(0.3201)	(0.3354)	(0.7321)	(0.5279)	(1.167)
DE, Post Nov 2015	-0.0458	-1.6205***	-0.5993	-6.0987**	0.6569	-2.3676	1.0675	-3.7177
	(0.3388)	(0.5917)	(1.2266)	(2.7215)	(2.6952)	(5.0389)	(4.2689)	(7.7901)
	Linguistic proximity:							
	Overall				*High-recognition*			
Variables:	ST Direct	ST Indirect	LT Direct	LT Indirect	ST Direct	ST Indirect	LT Direct	LT Indirect
Gdp per capita$_{(t-1)}$	0.9364***	1.0104	1.6104	6.4265	0.1704	-3.1196	0.4006	-4.097
	(0.3289)	(1.0912)	(15.0425)	(252.7673)	(0.8077)	(3.8491)	(1.2564)	(4.7803)
Unemployment$_{(t-1)}$	-0.0136	-0.0695	-0.0957	-1.2723	-0.0367	-0.1124	-0.0524	-0.1329
	(0.0339)	(0.0506)	(2.2881)	(38.4539)	(0.0635)	(0.2948)	(0.099)	(0.359)
Population$_{(t-1)}$	0.8293***	-0.1716	1.1432	1.94	-0.1478	-4.124	-0.0772	-5.1716
	(0.2407)	(0.6795)	(7.9468)	(133.7466)	(0.4079)	(2.6221)	(0.6157)	(3.2613)
Stocks of immigrants$_{(t-1)}$	-0.5417***	0.1446	-0.7731	-1.7931	-0.3015	0.8	-0.5207	1.1252
	(0.1823)	(0.5654)	(6.0452)	(101.7056)	(0.2774)	(2.0046)	(0.3913)	(2.4257)
Asylum presence	-0.2376***	0.0371	-0.3543	-1.0423	0.5357**	0.2335**	0.8716**	0.0925
	(0.0917)	(0.0572)	(1.5198)	(25.5353)	(0.2408)	(0.1082)	(0.4057)	(0.1447)
Tot. applications	0.0306	-0.1566	-0.0344	-1.0785	-0.5824***	-0.1579	-0.9467***	-0.0001
	(0.0558)	(0.1245)	(2.1994)	(36.9829)	(0.1201)	(0.3889)	(0.1917)	(0.5254)
Asylum, external borders	-0.1027	0.3634***	0.0885	3.273	0.1844***	1.3288***	0.2491***	1.5883***
	(0.0733)	(0.141)	(3.2139)	(54.0035)	(0.0761)	(0.4726)	(0.1066)	(0.5654)
Populism$_{(t-1)}$	0.2991*	0.2154	0.4837	1.6649	-0.6403	-1.7218	-0.9663	-1.8382
	(0.1676)	(0.5392)	(5.5108)	(92.5372)	(0.8382)	(3.501)	(1.3296)	(4.2278)
Social protetion$_{(t-1)}$	-0.0722	-0.0657	0.0816	2.921	0.6177**	3.4273**	0.8705*	4.0714**
	(0.1202)	(0.314)	(6.1732)	(103.7263)	(0.3036)	(1.5838)	(0.4677)	(1.9419)
DE, Post Nov 2015	-0.1123	-2.4776***	-1.9729	-28.4552	0.4447	-6.7313	0.9893	-8.904
	(0.3627)	(0.9497)	(29.5842)	(497.7174)	(2.7658)	(8.3407)	(4.5272)	(10.6126)

Notes: standard errors in parentheses. This table presents estimates of short term and long term direct and indirect effects of each explanatory variable on processing speed, as resulting from our baseline SPDP model with interactive fixed effects. For comparison, its related coefficient table is table 3.5.3. In the three subsections, from left to right, interaction matrices considered are based on geographic neighbors, linguistic neighbors. To compute these values, we use formulas proposed in Belotti et al., 2013, while uncertainty measures are developed based on the procedure suggested in J. LeSage and Pace, 2009 and P. Elhorst et al., 2013. Stars correspond to the following p-values: * $p < .10$, ** $p < .05$, *** $p < .001$.

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Concluding Remarks

This concluding chapter summarizes the main takeaways of this dissertation. It addresses some limitations of this work and briefly discusses some of the avenues for future research.

The first chapter studies whether and how diversity in the composition of groups affects group-level performance. Existing literature in economics (Ager & Brückner, 2013; Alesina et al., 2016; Ashraf & Galor, 2013; Docquier et al., 2019; Easterly & Levine, 1997) established that both benefits and costs arise from a diverse labor force. Individuals with different backgrounds potentially add value to the joint skill composition of labor, especially if they bring complementary and diverse skills. On the other hand, cooperation and efficient output could suffer if individuals' perceived differences lead to disagreements. We test the net effect on economic productivity by focusing specifically on the context of professional soccer in Europe. We build a dataset on European national teams, having participated in the European and the World Championships since 1970 and we propose a novel IV approach. The composition of a national team today is bounded by how diverse is the population. Therefore, we instrument the diversity of a national team at time t with the diverse composition of the population one cohort before. Crucially, we give importance to different distance levels across group origin groups. Following Arbatlı et al., 2020; Ashraf and Galor, 2013; Spolaore and Wacziarg, 2009, we use genetic distances to proxy perceived and actual differences across origins. Our findings indicate a robustly positive causal link between ancestral diversity and teams' performance. The main message of this paper is that diverse talent can be value-added in the joint production function of high-skill tasks, once we isolate diversity and by holding all other factors constant. It shall be acknowledged however that our finding is resulting from a particular setting, which is that of highly-professional sports in Europe. These results may not fully extend to other contexts where diversity heavily interacts with other important factors, where origin groups are hierarchically structured, or to sectors where skill complementarities are less relevant for productivity. Yet, we can conclude from this study that with the rise of migratory patterns in Europe, diverse talent bears an economic potential, with our result also offering a clear message against discrimination in European soccer.

Chapter 2 investigates how the salient events related to the European migration crisis impact the delivery of information around migration, with a focus on the local news supply and demand, and it documents how patterns in the news link with the local political economy. Existing literature suggests that the presence of migrants is positively associated with anti-immigrant attitudes and populist voting (Campo et al., 2021; Edo et al., 2019; Otto & Steinhardt, 2014).

On the other side, these individual preferences are also subject to the power of information delivered in the media sources (Djourelova, 2020; Gentzkow et al., 2019; Keita et al., 2021). This information, in turn, is not exogenous but rather depends on the preferences of readers (Gentzkow & Shapiro, 2006). This study bridges these two aspects and investigates the impact of migrant settlements in the context of the migration crisis on the size and discourse of migration-related news, distinguishing between supply and demand forces. This research exploits a quasi-random setting emerging from a specific policy enacted in June 2015. Starting from this period, French authorities introduced militarized controls at their borders with Italy, and pushed back several irregular migrants using this gateway to reach the French territory. On the Italian side, natives were more directly exposed to the presence of pushed-back migrants the closer to the borders they resided. Therefore, this study focuses on the Italian border region and assigns a treatment based on commuting distance from the border, within a difference-in-difference specification.

Results show that the backlog of migrants in the Italian border area increased the mediatic coverage of migration in the most directly exposed municipalities. At the same time, anti-immigrant discourse in the news is found to grow more in the areas further away from the border controls. Additional evidence suggests that this anti-immigrant discourse is driven by a demand channel: sources with the highest demand are most responsible for this effect, and penetration of local news follows the direction of anti-immigrant framing. Voting preferences and hate-crime records take broadly the same direction of anti-immigrant discourse, suggesting that what happens in the news also occurs at the level of the local political economy.

To summarize the main takeaway of this study, natives may react unfavorably to the presence of migrants and demand information that accommodates their ideology. The higher hostility, however, results where natives are only indirectly and partially exposed to the settlement of migrants (Allport, 1954; Steinmayr, 2021). Additionally, this work highlights the importance of considering the endogeneity driven by demand in studies on the persuasive power of media. Finally this paper raises attention to the internal EU borders as areas strongly impacted by the migration crisis and where international cooperation is not self-evident.

It shall be kept in mind that these results are specific to a geographic context that is already less favorable towards migration (as reflected in pre-existing voting preferences in this area). So such effects could be milder in areas where natives have a more positive ideology in the first place. Additionally, this study is limited to the examination of anti-immigrant slant as a binary variable: news articles are only categorized as anti-immigrant or not, following their similarities with national or regional newspapers with known ideology. A more comprehensive approach would allow for greater complexity, for example by adding also a pro-immigrant slant, versus a neutral category. The binary choice was the simplest and most tractable procedure, but further advancements in text analysis and big-data technologies may allow future research to capture greater nuances.

Chapter 3 investigates the role of cross-countries interdependencies in explaining policy decisions on asylum reception.

The last two decades saw several efforts of the European Union toward the construction of a common asylum system. Despite these steps, anecdotal evidence suggests that the adoption of uniform procedures in each country is still far from reality.

In this paper, we adopt a spatial econometrics model to investigate whether country decisions on the reception of migrants in the asylum crisis influence and are influenced by the choice of their most closely connected neighbors.

As asylum seekers tended to undertake journeys that involved the crossing of several countries through specific routes, geographic proximity would capture the directions of potential leakages and deflections of migrants induced by a policy change. Expecting these leakages, neighboring countries would then be more sensitive to the events occurring at their borders, than to those further away. With our empirical strategy, we test the null hypothesis that the spatial arrangement of policy decisions is random. The alternative is that the spatial arrangement follows geographic (and/or linguistic) proximity, which we motivate as signaling a cross-neighbor reaction in asylum receptions. In our dynamic spatial panel data model specification with interactive fixed effects (Shi & Lee, 2017), we partial-out the (possibly heterogenous) effects of unknown common factors, that lead to a strong cross-sectional dependence in the data and confound the role of spatial effects. While interactive effects absorb heterogeneous impacts from common shocks on cross-section units, idiosyncratic factors may also confound the degree of local interdependence, if they exhibit spatial correlation and vary with time. Therefore, we control for a set of covariates and their spatial lags, these terms capturing neighborhood-level changes that lead to potentially similar simultaneous reactions. Our results show the importance of considering strong cross-sectional dependence in spatial models. Spatial relations differ substantially in size and significance, once we have controlled for interactive effects.

Results show asylum policies are strategic substitutes, with key results in both dimensions of interactions. Finally, we document spillover effects emerging from Germany's reception announcement in September 2015 on cross-country processing speed, as well as significant indirect effects resulting from the arrivals of migrants at the external EU borders. Summarising the main takeaways, we find evidence that neighborhood interactions exist when it comes to the decisions of countries on their reception of asylum seekers.

Importantly, we do not claim full causality in our findings, as we are unable to discard all possible sources of endogeneity in our results. We consider several covariates that may suffer from endogeneity and whose marginal effects may not be consistently estimated. Still, our methodology is a step forward from a scarce and heavily descriptive literature that has been facing several empirical difficulties both in the measurement and the estimation of such cross-country effects.

Although less originally, it is important to highlight that future research would greatly benefit from comprehensive data on migration policy openness. Existing efforts either present a very low variation cross-country and/or over time, or fail to capture fully the multi-dimensionality and complexity in migration policies.

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