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Diversity and polarization between natives and immigrants: the case of Barcelona

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Abstract

The scope of our research is to conduct an empirical investigation into the degree of ethnic cohesion in a multiethnic city such as Barcelona (Spain). Our aim is to assess how immigrant and native groups are distributed across the city's neighborhoods and understand their locational patterns in order to identify potential polarization trends that could undermine socioeconomic cohesion among citizens. Unlike much of the existing literature, we adopt a research strategy based on spatial analysis. Our findings indicate that, between 2008 and 2020, Barcelona experienced a decrease in polarization and an increase in diversity—understood as the co-location of different communities—at the neighborhood level. Income emerges as a relevant determinant: it is associated with lower diversity and positively correlated with polarization. We identify that high-income neighborhoods are predominantly inhabited by natives and Europeans, while other communities are relegated to peripheral areas, which in turn become more diverse. However, this distribution pattern is reinforced by the linguistic and religious distance. A deeper interpretation of our results suggests that initiatives aimed at fostering human capital development and education could serve as effective tools to promote a more balanced spatial distribution of communities that could enhance urban social cohesion.

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1. Introduction

A growing body of literature shows that the risk of a cultural divide flourishing in modern societies is mostly associated with the rising intensity of international migration flows. The cultural divide is a true concern for policy makers since it creates socio-economic conditions among communities in a society that could harm not only the inclusion process (with social conflicts, for instance), but also limiting the perspective for socioeconomic development or welfare.[2] The crucial factor driving a negative effect associated with the cultural divide is linked with the likelihood of interaction that can or cannot be established among different communities and, in particular, between natives and immigrants. If that interaction takes place, then the likelihood of achieving social cohesion and possibly limiting the potential drawbacks for polarized or segregated societies is relatively high.[3] The urban context is an interesting spatial setting to explore the potential variation in the degree of the social integration given the variation of the size and number of communities living in a city. The urban dimension allows for a better approximation of the possible interaction conditions among different communities conditional on a series of (common) environmental factors for all individuals belonging to the different communities, but this has been barely explored.

A basic condition to implement successfully this type of approach is having the possibility to identify an urban setting characterized by a minimum degree of heterogeneity in terms of number of communities settled in its premises. From this perspective, the application of such a framework of analysis the city of Barcelona is extremely appropriate. Since the beginning of the 20th century, Barcelona has ranked among preferred destinations of national and international migrants alike (Garcia-López et al. 2021). The city currently hosts important, diverse ethnic groups of immigrants, a condition that makes it vulnerable to the possible creation or consolidation of important segregation effects that can precipitate the fragmentation of urban society (Borjas, 1998), with all of the potential consequences of social instability, as can be perceived when examining other cities, for instance, in Europe (Musterd at al. 1997).[4]

[2] De Graaff and Nijkamp (2010) conclude that migrant clustering generates negative effects on socio-economic welfare for Dutch cities mostly driven by an excessive degree of diversity.
[3] Under a similar perspective, Rodriguez-Pose and Berlepsch (2019) conclude that population diversity can be an asset for economic development.
[4] Throughout the study, the ethnicity of each group of immigrants is identified according to their place or country of birth.

The scope of our research is to analyze the spatial co-habitation of communities in Barcelona given their number and size by focusing on economic features and cultural traits. Our target is to assess the extent in which groups of immigrants and natives may chose similar pattern of location in a city (referring to the place of residence) by identifying a few of the potential socio-economic and cultural factors that contribute to shape that distribution and, indirectly, fuel spatial integration among communities.[5]

Unlike in the literature, we adopt a research strategy that relies on spatial analysis.[6] Because we need to approximate the idea of interaction among individuals as a driving force for the integration and/or segregation of groups of citizens, the spatial dimension is fundamental to be taken into account. The idea of the physical location of each individual and its spatial proximity to others (i.e., natives or immigrants of the same or different ethnic group) are key features for identifying possible interactions among individuals. Two individuals whose place of residence is in the same city *barri* ('neighborhood') are more likely to interact than two individuals living in distant *barris*, albeit depending on their own propensity to socialize. In that respect, our analysis stems from the previous contribution of García-Lopez et al. (2020) and augments that framework of analysis by including indicators that embed the cultural dimension of different urban ethnic groups. The novelty of our approach is to build selected indicators that could help to approximate the combination of the spatial distribution of the different ethnic communities in the city. We elaborate a few indices: the diversity index, the polarization index, as well as the language, genetic and religious distance (as in Spolaore and Wacziarg, 2016) for each principal group of migrants versus natives. Our empirical analysis assesses that income has an important role in shaping the territorial distribution of each community of immigrants and generates a rather polarized picture with a clear pattern of assimilation of high-income groups to natives whose preferred location turn to be the central neighborhood of the city, whereas the biggest share of migrants is relegated to the (low-income) peripheral spatial units. Religion and language distance of each (ethnic) group are exacerbating the relegation of selected communities in the periphery, and hence, harming the social cohesion. Under these circumstances, and referring to the literature (Griliches and Mason, 1972) it seems that education helping to increase human capital (and, hence, income) as well as shrinking the language distant can act as a deterrent for the uneven territorial distribution of the

[5] The benefits of cultural diversity have also been exploited by the literature as a further trigger for economic growth (Bove and Elia, 2017 or Rodriguez-Pose and Berlepsch, 2019).
[6] The spatial analysis has already been exploited in similar setting like the analysis of social exclusion (Cartone et al., 2024) or well-being analysis (Giacalone et al. 2025).

communities in the city. In terms of territorial public policies, targeting education could be an effective trigger for social cohesion in an urban setting like Barcelona.

This study is structured as follows. In Section 2 we propose a brief literature review whereas in Section 3 we introduce our two main indicators and in Section 4 we present descriptive statistics of our database. In Section 5 we outline our empirical exercise and Section 6 we add some extensions and, finally, Section 7 concludes. Further information is included in the Appendix.

2. Literature review

The idea of cultural diversity (at any spatial level) is strictly connected with the idea of a multicultural society stemming from the presence of migration flows. The size and direction of migration flows are often driven by *push and pull* factors analyzed in a gravity-style framework. For migrants, the attractiveness of a destination mostly relies on origin-destination specific factors (like income, migration policies, or environmental factors), but also so-called *dyadic* factors like linguistic or cultural proximity or network ties between a community in a host country and population in the country of origin (Adserà and Pytliková, 2015; Beine et al., 2016). Therefore, the cultural dimension (and in particular the cultural distance between the origin and destination countries) is a crucial determinant either for the selection of migrants' destination county and for the degree of socio-economic cohesion in destination countries as well.

The rise of culturally polarized societies, magnified by recent trends such as the diffusion of social media, has been identified as part and parcel of the recent, unprecedented growth in political discontent, populism, and skepticism toward institutions (Donni et al., 2021; Levy, 2021; Gethin et al., 2022; Guriev and Papaioannou, 2022). To pinpoint the determinants of that phenomenon, scholars have studied the evolution of cultural heterogeneity in modern societies, mostly the United States, in search of sources of cultural cleavage across individuals (Desmet et al., 2017).[7] By focusing on specific identity cleavages, including education, ethnicity, and partisanship, Desmet and Wacziarg (2021) have explored whether individual identities are good predictors of the heterogeneity of individuals' values and attitudes toward various dimensions: gender equality, homosexuality, abortion, confidence in situations or political attitudes among others. If identity cleavages are

[7] Such literature acknowledges that culture and cultural diversity are broad concepts that encompass many different values and traits (Kroeber and Kluckhohn, 1952).

a good predictor of cultural heterogeneity in societies, then the polarization of culture is driven by the distinctive stance taken by each specific group. Interestingly, published results show that cultural heterogeneity cannot be explained by any polarization between different identity traits but is rather influenced by within-group heterogeneity in identity. Similar results have also been reported by Bertrand and Kamenica (2018).

Despite those reassuring results, the literature often overlooks the role played by immigration, both as a form of identity cleavage in explaining the evolution of cultural heterogeneity and as a potential determinant of the evolution of attitudes and values. However, immigration can also be a source of cultural change and tension in several dimensions, as highlighted by Rapoport et al. (2020). First, by coming from countries with distinctive norms and institutions, immigrants can influence host societies via a simple compositional effect. Echoing the concerns of Collier (2013), immigrants can influence the cultural heterogeneity of host society simply by mixing with the host population: "Uncomfortable as it may be [...] migrants bring their culture with them" (Collier, 2013). Luttmer and Singhal (2011) have additionally shown that migrants from countries with strong preferences for redistribution support parties with similar preferences. In earlier work, Fernandez and Fogli (2009) found that immigrants' fertility-related preferences in the United States are related to norms in their country of origin. Moreover, immigration can influence societies in host countries by introducing a diverse mix of competences, skills, and values. Alesina et al. (2016) and Docquier et al. (2020) have shown that diversity in birthplaces within the immigrant population, used as a proxy of the diversity of competences, positively affects countries and regional economic growth, as explained by the expansion of a production-specific knowledge set (Bahar et al., 2022). However, less is known about the potential implications of a diverse immigrant population on the cultural heterogeneity of societies.

Immigrants can also influence societies in host countries by sharing their experiences in their home countries with the host population in a process referred to as *cultural dissemination*. In recent empirical literature showing evidence of that potential route, Giuliano and Tabellini (2021) have found that immigrants to the United States during the Age of Mass Migration who originated from European countries where social reforms had been enacted in the 1800s ultimately shifted the political preferences in destination counties in the United States toward more social spending and public education. Along similar lines, Levai and Turati (2025) have shown that the regulation of workers' protections in host societies is influenced by immigrants' experiences with labor market institutions in their country of origin. Miho et al. (2020) have additionally shown that Russian regions that welcomed German immigrants amid Stalin's deportation during World War II currently espouse relatively gender-egalitarian attitudes and values, given the egalitarian views of Germans compared with the other ethnic groups in the communities in which they integrated.

Nevertheless, immigration does not necessarily affect cultural values, for immigrants can assimilate into the host society's culture. Several studies have highlighted the assimilation of immigrants in the United States during the last century (Abramitzky et al., 2020), particularly in their adoption of American-sounding names or intermarriage rates, which have been used as proxies to capture immigrants' assimilation (Biavaschi et al., 2017; Fouka et al., 2022). Moreover, the literature shows that the degree of immigrants' assimilation is affected by the degree of assimilation of the ethnic network. Exploiting the quasi-exogenous placement policy of the Norwegian refugee resettlement program in the 1990s, Bratsberg et al. (2021) have shown that refugees' electoral participation is affected by the political engagement of their peers in the arrival location. In the same vein, relying on block-level variation for the city of New York between 1930 and 1940, Biavaschi et al. (2021) have found that immigrants' naturalization process is influenced by the number of co-ethnic naturalized immigrants in the same block. In the wake of the current discussion in the literature, in this contribution, we aim at providing further insights about the association between the ethnic composition of urban citizens, discrimination, and cultural cleavage. In order to perform our analysis, we implement an original empirical investigation for which we elaborate key indicators for diversity, polarization, language, religious, and genetic distance.

3. Diversity, polarization, language, religious, and genetic distance: an empirical approximation

We are aiming to disentangle the factors that can influence – over time- the size of the index of diversity, polarization, as well as language, genetic and religious distance at urban level (for the case of Barcelona) by referring to factors portraying the urban socioeconomic conditions but also taking into account the cultural distance between the origin and destination place for each foreign community settled in Barcelona.

In order to perform our analysis, we need to compute various indicators or cultural similarity or dissimilarity among groups embedding different features of the cultural dimension.

As for the cultural proximity, we follow the literature (e.g., Alesina et al., 2016, and Giuliano and Tabellini, 2021). We measure two dimensions of immigration: size and composition. Nonetheless, it is relevant to recall that immigration is a complex phenomenon, hence we can only rely on proxies to quantify its different facets.[8]

Given statistics at hand, we are able to build the following indicators.[9] Concerning the size of the immigrant population, for each *barri* s at year *t* we compute the *share of immigrant population* over the native as follows:

$$m_{s,t} = \frac{Mig_{s,t}}{Natives_{s,t}}$$

where *Mig* is the total number of immigrants and *Natives* is the total population. The share of immigrants can be zero (i.e., a *barri* without immigrants) or positive; when the index is larger than one, we are dealing with a *barri* where the total number of immigrants is larger than the number of natives living there.

Although being a self-selected group with respect to their origin country population, immigrants are not fully orthogonal to their origin country characteristic, norms, and values. To explore the origin-specific dimension of the immigrant population, we follow the literature investigating the consequences of immigration from specific origin countries or regions (Collier, 2013; Miho et al., 2020) and we also compute a version of the previous index by the following origin-specific migration share ($m^o_{s,t}$). In this last case, the numeration is the total number of immigrants is now from a specific country of origin or region *o*.

Finally, to capture the heterogeneity of skills, competences and values brought by immigration, we compute a birthplace diversity index (Docquier et al., 2019; Bahar et al., 2022) for each *barri s* at year *t* over the immigrant population as follows:

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[8] Trying to confine immigration as an economic or labor market specific phenomenon would be short sighted. Quoting Max Frisch, a Swiss Novelist of the 50s', talking about the guest workers program in Germany: "We wanted workers…but we got people instead."

[9] We are basically referring to two datasets (at *barri* level) released by Ajuntament de Barcelona that is not always possible to handle jointly (*Barcelona dades; Moviments Demogràfics*) but each of them allows for taking into account different and relevant characteristics of the composition of the immigration flows.

$$Div_{s,t} = \sum_{o=1}^{O} \overline{m_{s,t}^{o}}\left(1 - \overline{m_{s,t}^{o}}\right) = 1 - \sum_{o=1}^{O} \left(\overline{m_{s,t}^{o}}\right)^{2}$$

The $\overline{m_{s,t}^{o}}$ is the share of immigrants from origin country *o* ∈ *{1, … , O}* over the total of immigrants in *barri s* at year *t*. Hence, the birthplace diversity index of immigrant population proposed right above is an Herfindal Index which measures the probability to randomly draw two immigrants from the immigrant population born in two different countries. The value of the birthplace diversity index can span from zero (i.e., all the immigrant population is coming from one unique country of origin) to one (i.e., uniform distribution of the immigrant population across origin countries). As it is has been shown by the decomposition proposed in Alesina et al. 2016, to capture the composition of the immigrant population the birthplace diversity index has to be computed over the immigrant population and not over the total population (i.e., including natives), because the birthplace diversity index over the total population would be highly correlated with the immigration share $m_{s,t}$.

In the same wake, we compute the *polarization* index for the spatial unit *s* at time *t* (the Reynal-Querol index [10] as in Doquier et al. 2019):

$$PI_{s,t} = 1 - \sum_{o=1}^{O} \left(\frac{0.5 - m_{s,t}^{o}}{0.5}\right)^{2} m_{s,t}^{o}$$

When PI_{st} approaches to zero, it implies that there are various sizable ethnic communities in each spatial unit whereas when the location *s* concentrates a unique (or a limited number of) community(ies) the index approaches to 1 (and the highest value is achieved in correspondence of a bipolar symmetric distribution). Furthermore, the index is strictly decreasing with respect to the number of the communities hosted in a location.

Another important dyadic determinant for the cultural cleavage is the *language distance* between a community of immigrants and natives: the impossibility of communication is expected to exacerbate the cultural cleavage. Additional cultural factors as religion can also harm the social cohesion. Spolaore and Wacziarg (2016) propose a general index-formula to compute the relative distance of selected dyadic variables *(DV)* of cultural cleavage (alternatively, linguistic distance, religious distance, and genetic distance). We leverage these indices to propose an alternative metric that captures the magnitude of migration, weighted by the three different DV distances for each group of migrants *o* with respect to natives:

[10] Reynal-Querol (2002)

$$RD_{s,t} = \left(\frac{\sum Mig_{s,c,o,t} * DV}{Total\ \boldsymbol{natives}_{s,t}}\right)$$

in which c stands for the continent the country o belongs to.[11]

The idea is to build an index that approximate the percentage of immigrants speaking another language (or practicing another religion or having a different genetic map), for instance, with respect to natives in a *barri*.[12] One advantage of these proxies is that they do not just capture distances between two languages (or religion or genes) but they account for the fact that an observed country may have different subpopulations that embed different religions, languages, and genes. They do so by using ethnic composition data to calculate the distances, rather than just relying on population. For example, Italy embeds not just 'Italians', but also other ethnic groups such as 'Rhaetians' and 'Sardinians'. Spolaore and Wacziarg (2016) match all these ethnic groups into one generic category 'Italian'. Thus, the weights for DV can be interpreted as the expected language (or religious or genetic) distance between two randomly selected individuals, one for each country.

4. Empirical evidence

To perform our empirical analysis, we gathered data from the official archives of the Ajuntament de Barcelona.[13] Our final database covers 2008–2020 and is fully balanced.[14] We have data covering the entire period that refers to the total population (and gender composition), as well as the number of total immigrants intended as Barcelona citizens born in a foreign country (stock data by country and year).[15]

[11] In order to get more tractable results in the estimation, the total number of natives is computed in thousands.

[12] When referring to the linguistic distance, we have to implement a key working assumption. Barcelona is a bilingual city where Catalan and Spanish coexist. The original data for the language distance in Spolaore and Wacziarg (2016) does not include Catalan and, therefore, our indicator is built by using Spanish as a language for reference for natives in Barcelona.

[13] Due to data availability constraints, it was not possible to include all municipalities of the Barcelona Metropolitan Area in the analysis. Several municipalities near Barcelona host significant migrant communities. However, the fine-grained geographical unit of analysis used in our study (at the neighborhood level), which is crucial for our approach, could not be consistently applied to these municipalities throughout the entire study period. As a result, we were compelled to limit the analysis to the city of Barcelona. Despite this limitation, Barcelona remains a highly representative destination for immigrants, as shown in Figure 1.

[14] Our sample is composed by 73 *barris* (neighborhoods) for 12 years.

[15] In this study we refer to regular immigrants only since they are the ones included in the official administrative records (*Padrón*)

Figure 1 illustrates the average migration rate by continent of origin. For most regions, emigration shows an increasing trend over time, with the notable exception of migrants from the Americas, whose average share per *barri* (neighborhood) declines. This reduction may be attributed to the adverse effects of the 2008 financial crisis, particularly on Latin American migrants, many of whom may have returned to their home countries or relocated to other destinations. The year 2014 appears to mark an inflection point in migration trends. This year saw either an acceleration in inflows from Asia and Europe or a reversal of the downward trend in migration from the Americas. This shift is likely linked to Spain's economic recovery, particularly driven by growth in the service sector.

To provide a more detailed migration profile, Figure 2 presents the countries with the highest proportion of migrants from each continent. A clear contrast emerges between migration patterns from Asia and Africa compared to those from Europe and the Americas. Migration from Asia and Africa tends to be concentrated among a few countries: for instance, Moroccan migrants represent nearly 10% of African migration, while individuals from Pakistan and the Philippines each account for about 8% of Asian migration. In contrast, migration from Europe and the Americas is more evenly distributed. For example, Italian migrants make up less than 2% of European migration, while Bolivian and Honduran nationals each represent under 1% of migration from the Americas. To sum up, migration from Asia and Africa is characterized by dominant flows from specific countries, whereas European and American migration exhibits a more heterogeneous and balanced composition.

Figure 1. Migration trends

Source: Own database; Calculus: Authors

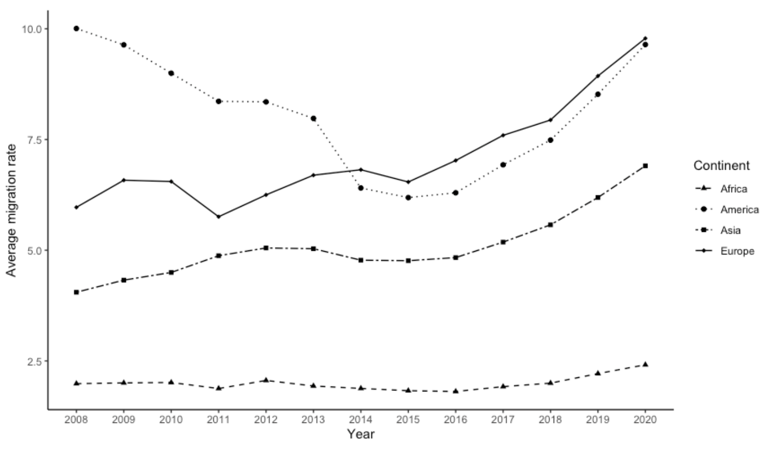
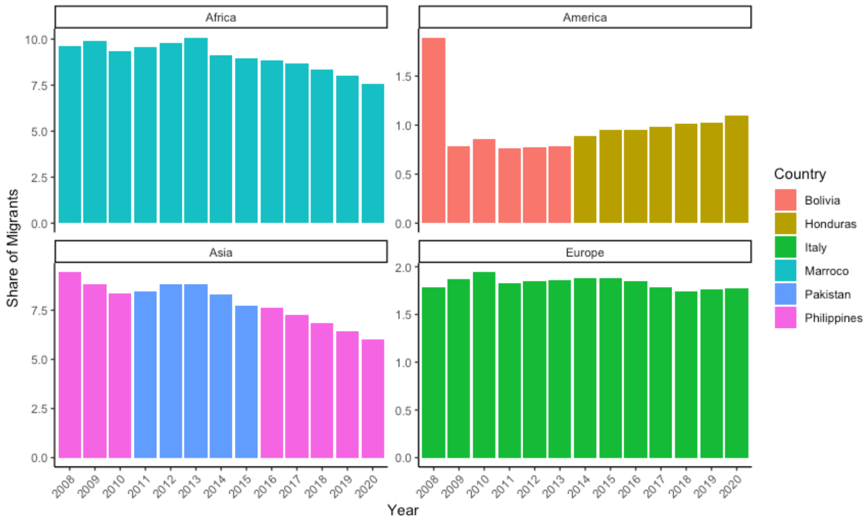


Figure 2. Group of migrants

Source: Own database; Calculus: Authors



We begin by exploring the content of our database, namely by building indexes referring to the composition of the group of immigrants versus natives. The descriptive statistics of those indicators are included in Table 1, in which one can also appreciate the number of observations at our disposal. In Table 1, we present the average value of all indicators across time and spatial units, whereas Figures 3–7 focus on the two extremes of the period under analysis. Referring to Table 1, it is worth highlighting the statistics on polarization. Barcelona exhibits a significant degree of heterogeneity across its neighborhoods, with some areas hosting diverse immigrant communities (polarization index: 0.132), while others are more selective (index: 0.615). This considerable variation is reflected in other measures such as linguistic, religious, and genetic distances. A similar pattern is also observed in the index of available income, suggesting the existence of strong spatial disparities. In contrast, the diversity index—whether measured by country or continent of origin—shows less variation across neighborhoods. These findings suggest a close association between polarization and income inequality at neighborhood level.

Table 1. Descriptive statistics

Source: Own database;[16] Calculus: Authors

Variable	Mean	Std. dev.	Min	Max	Observations
Diversity index by continent	0.649	0.054	0.405	0.748	803
Diversity index by country	0.939	0.027	0.704	0.965	803
Polarization index	0.212	0.069	0.132	0.615	803
Relative distance, RD (language)	0.169	0.135	0.031	1.257	803
Relative distance, RD (religion)	0.129	0.099	0.024	0.963	803
Relative distance, RD (genetic)	0.024	0.017	0.005	0.124	803
Index of available income - Family disposable rent index (RDF) (100: average Barcelona)-	0.925	0.391	0.343	2.517	803
Number of employees per household (average)	2.516	0.186	2.15	3.28	803
Population density (hectare)	6.865	37.20	0.007	398.32	803
Share of immigrants (Total)	0.223	0.167	0.044	1.642	803
Share of immigrant woman	0.205	0.132	0.043	1.094	802
Share of immigrant man	0.244	0.205	0.039	2.191	802
Share of African Immigrants	0.020	0.023	0.000	0.157	803
Share of American immigrants	0.078	0.040	0.019	0.295	803
Share of Asian immigrants	0.053	0.078	0.002	0.698	292
Share of European immigrants	0.073	0.067	0.005	0.534	803
Share of women	0.518	0.023	0.437	0.600	803

[16] As argued in footnote 5, the different data sources prevent from the possibility for cross-comparison of indicators.

The first indicator we discuss is the share of immigrants (Figure 3), computed as the total number of immigrants over the total population of natives in each *barri* in Barcelona ($m_{s,t}$).[17] In that way, we can make an initial appraisal of the relative territorial concentration of immigrants. We can also break down the indicator by gender (i.e., distinguishing men from women), the results of which appear in Figure 3.[18] Overall, the average share of immigrants is approximately 22% (Table 1), a value that changed over time owing to the effects of the financial crisis experienced in 2008. In terms of size, no structural differences arise between men and women; however, women tend to be more concentrated in selected *barris* in Les Corts and Ciudad Vella, whereas men are more equally distributed over the urban territory, with significant clustering in Ciudad Vella and some nearby *barris* in the Eixample.

Probing the ethnic dimension of the composition of the group of immigrants versus the group of natives, we map their spatial distribution by splitting them according to the continent of origin.[19] The results are presented in Figures 2–5, in which the groups considered are Africans (i.e., mostly from the Maghreb region, around 2% of the population), Americans (i.e., mostly from Latin American countries, around 8%), Asians (around 5%), and Europeans (around 7%). The largest community of immigrants is Americans, followed by Europeans. The spatial distribution of Europeans and Americans has remained mostly unchanged over time, whereas Africans have consolidated their concentration in peripheral areas as well as established important clusters in the Eixample.

Three distinct patterns can be observed. First, Africa and Asia migration tends to concentrate in the same marginalized *barris* over time, forming clearly identifiable clusters in peripheral districts. Second, European migrants are predominantly located in central *barris*, which are typically characterized by higher income levels. Third, migration from the Americas displays a somewhat different distribution: while these migrants are also concentrated in peripheral areas, there is a noticeable presence in *barris* adjacent to higher-income neighborhoods.

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[17] Figures 1-7 maps the distribution of flow data for immigrants; they embed the possible change of pattern distribution across time by focusing on flow data that embed both the internal migration across *barris* and new incoming immigrants in Barcelona.

[18] Information about the name and distribution of *barris* in Barcelona appears in the Appendix.

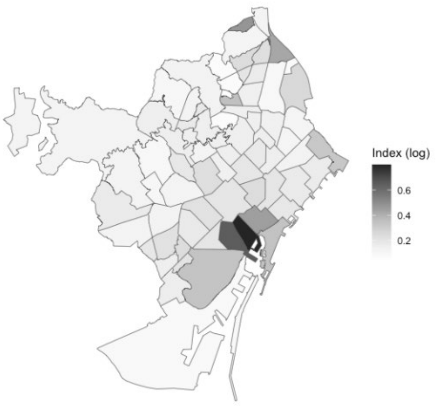
[19] The source of data by country of origin differs from the one referring to the total number of immigrants. Whereas the former is available for even years only, the latter is available for all of the years. For those reasons, the numerical indices are not comparable.

In the Appendix (Figure A1), we present the LISA statistics. These statistics confirm the distribution patterns we discussed for each group of migrants. High-high clusters are observed in *barris* close to those where European migrants are concentrated. This pattern may support the argument that Latin American migrants tend to settle near the neighborhoods where they are employed. Such spatial clustering could be partly explained by their relatively greater cultural and linguistic affinity with European populations, which may ease their integration into service-sector roles—particularly in caregiving positions involving children and the elderly.

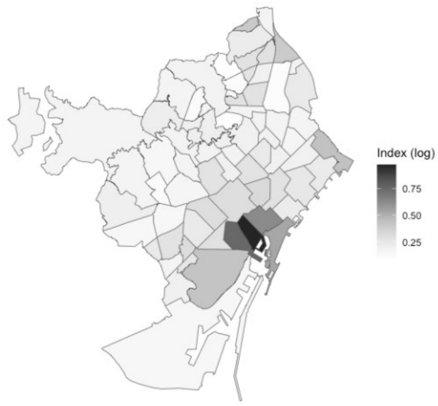
Figure 3: Share of immigrants
Source: Own database; Calculus: Authors

Total

2008

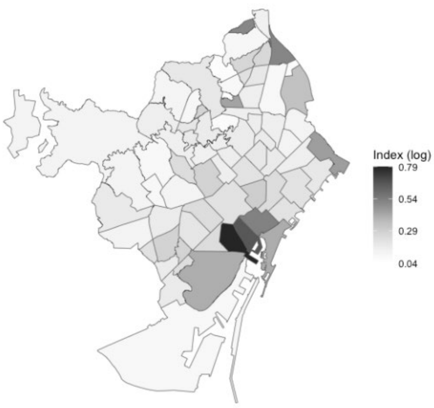


2020

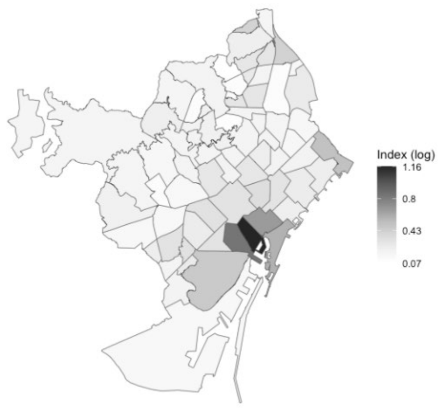


Man

2008

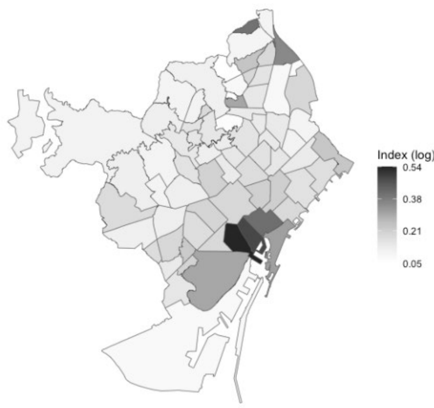


2020



Woman

2008



2020

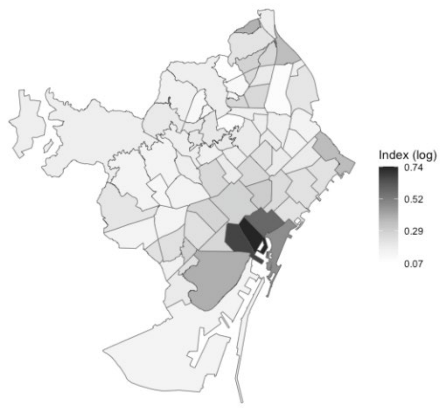


Figure 4: Share of immigrants -Africans-

Source: Own database; Calculus: Authors

2008 2020

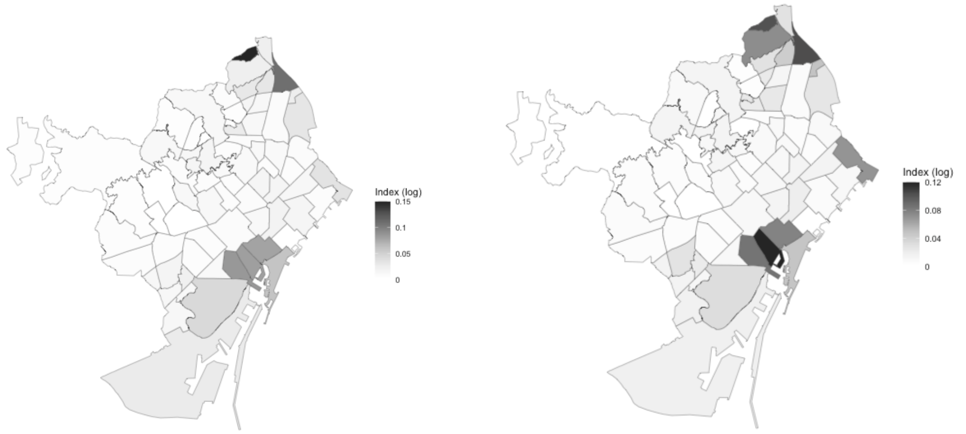


Figure 5: Share of immigrants -Americans-

Source: Own database; Calculus: Authors

2008 2020

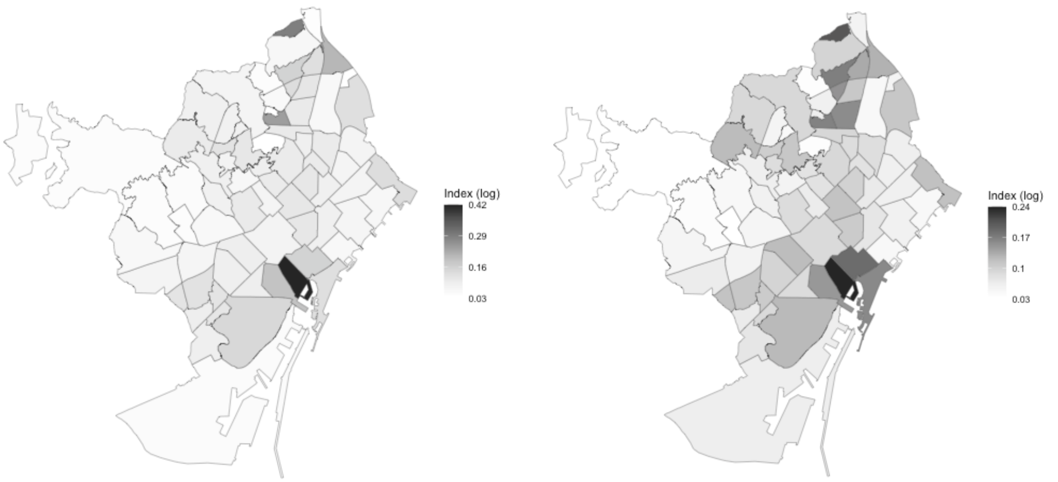


Figure 6: Share of immigrants -Asians-

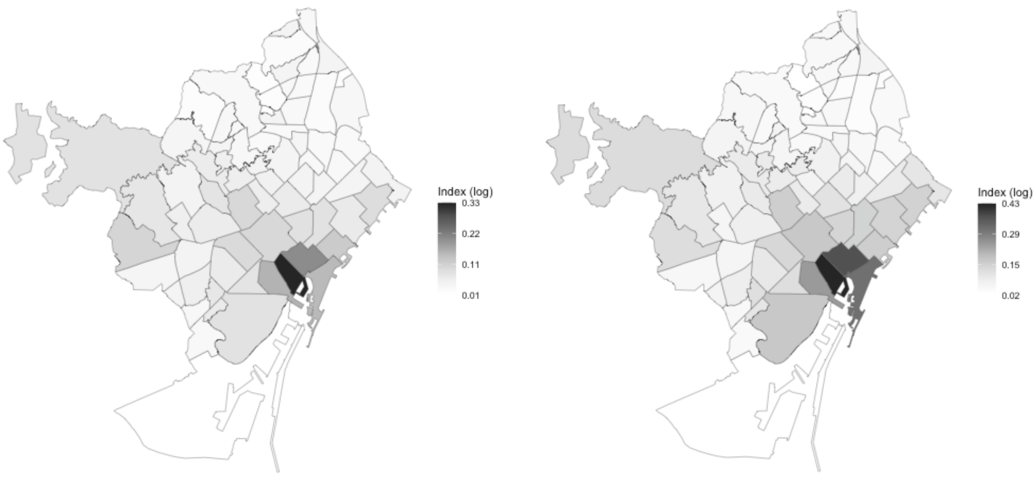
Source: Own database; Calculus: Authors

2008 2020

Figure 7: Share of immigrants -Europeans-

Source: Own database; Calculus: Authors

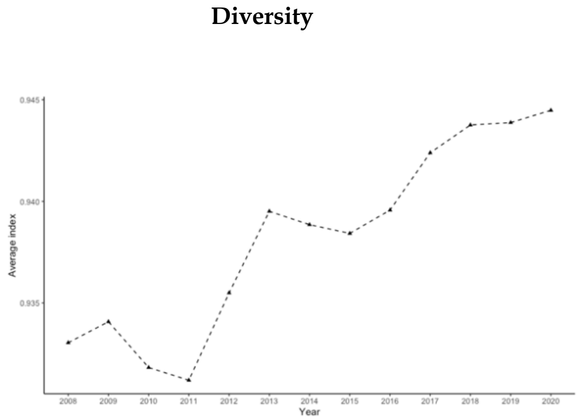
2008 2020

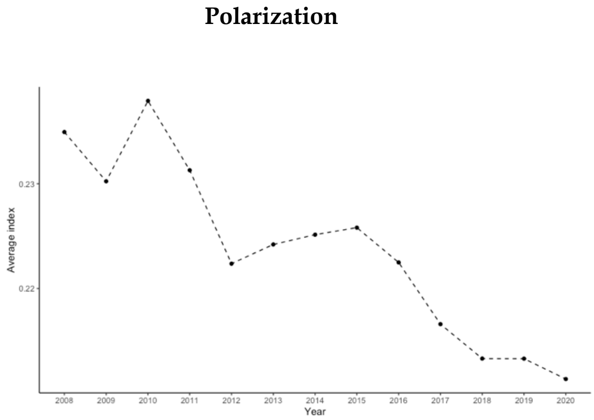


The last two indicators that we analyze are the diversity index and the polarization index.

Figure 8: Diversity and Polarization trends

Source: Own database; Calculus: Authors





Our statistics confirm that -over time- the index of diversity increased in Barcelona whereas the polarization decreased (Figure 8). One feature to emphasize about average polarization is that it has not reached high values over time, with the highest one in 2010 of around 0.24. The distribution of this polarization is again concentrated in peripheral districts, where most African and Asian (being mainly Morroco and Pakistan) locate. Higher diversity, on the other hand, seems to be concentrated in central *barris* (Figure 9), suggesting that this diversification is mainly driven by Europeans and Americans who, due to their closeness in language and culture, choose to locate in neighbouring districts, while the rest of the migration tends to be polarized in marginal areas (Figure 10).

Figures 11, 12, and 13 partly support this argument. They show the areas that cluster the share of migrants with the highest distances in language, genetics, and religion relative to natives, as measured by our weighted indices. Clearly, those areas with the biggest distances are the ones with the lowest diversification. The intuition would be that Europeans and Americans, relatively closer in terms of language, culture, etc., choose to locate in higher-income areas, leaving the rest of the migrants aside.

Figure 9: Diversity index (by country)

Source: Own database; Calculus: Authors

2008 2020

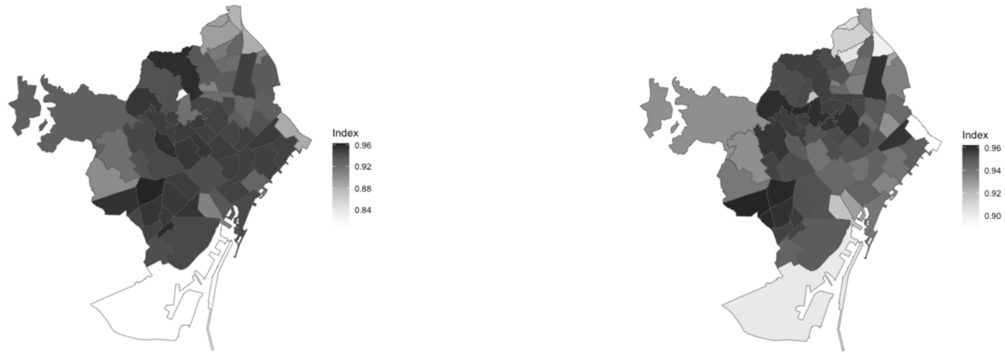


Figure 10: Polarization index (by country)

Source: Own database; Calculus: Authors

2008 2020

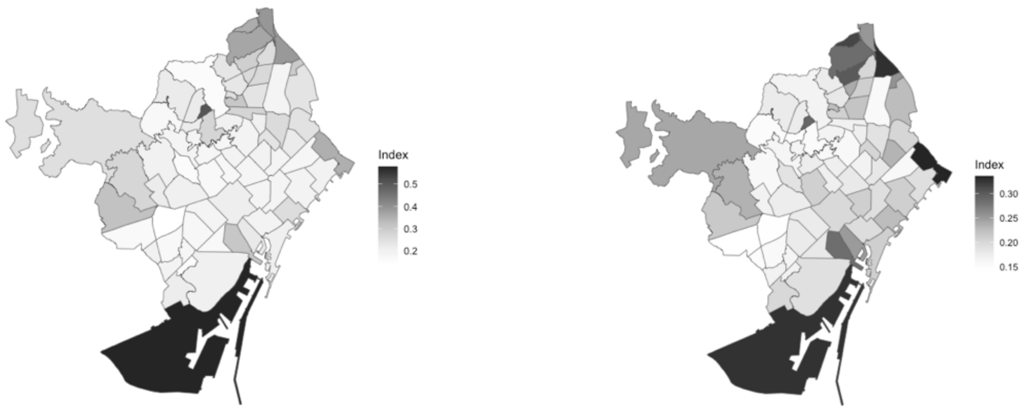


Figure 11: Relative distance (language)

Source: Own database; Calculus: Authors

2008 2020

Figure 12: Relative distance (religion)

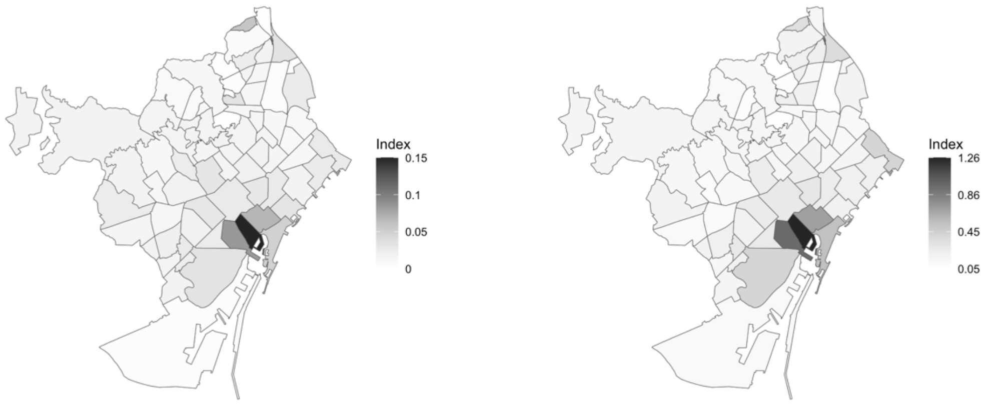
Source: Own database; Calculus: Authors

2008 2020

Figure 13: Relative distance (genetics)

Source: Own database; Calculus: Authors

2008 2020



An interesting preliminary intuition stemming from the descriptive analysis is to consider income as a synthetic measure able to shape the spatial distribution of the diversity and polarization index. If so, one could also expect that income can drive the temporal evolution of the two indexes and, eventually, exacerbate discrimination patters. In order to be more conclusive on this question, we propose a simple β- convergence estimation (Table 2) to learn whether there has been a possible convergence of the diversity and polarization indexes across the neighborhoods in Barcelona.[20]

[20] Barro and Sala-i-Martin (1992)

Table 2: Convergence trend across neighborhoods

	Growth rate Diversity	Growth rate Diversity	Growth rate Polarization	Growth rate Polarization
Diversity index 2008	-0.0515***	-0.0500***		
	(0.0044)	(0.0037)		
Index of available income 2008		0.0007*		-0.0047
		(0.0004)		(0.0043)
Polarization index 2008			-0.0222***	-0.0330***
			(0.0072)	(0.0050)
Obs	73	73	73	73
R-squared	0.647	0.723	0.105	0.372
AIC	-785.0814	-809.5593	-391.8400	-449.9925
BIC	-780.4733	-802.6879	-387.2319	-443.1212

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

In both cases, the indexes recorded an absolute convergence process across the *barris*: this dynamic implies that a sort of shared evolutionary trend among the different urban neighborhoods to achieve (converge to) similar characteristics. The convergence process is slightly lower in polarization than in diversity. However, the most interesting results of these estimations are that the income does not play any role in the dynamic tendency (the estimated coefficient is slightly significant for diversity only); hence, other determinants are expected to drive the spatial changes in polarization and diversity among communities in Barcelona.

Finally, a common feature that emerges in Figures 4–7 is the potential existence of spatial dependence, given the clear spatial persistence of the different areas of clustering. Indeed, wherever each category of data records a high degree of concentration, there are always spatial units with a sizable degree of concentration, though the effect fades across space. That type of distribution signals the possible existence of spatial dependence, and if it does exist, then the econometric strategy has to adapt in order to avoid biased estimation results. The existence of such spatial dependence can be assessed by computing the Moran index, which if statistically significant confirms the existence of spatial dependence.[21]

Table 3 presents the results of the Moran index and its degree of statistical significance at level of *barri*. As shown, the values of the index as well as their statistical significance are particularly high. Because those results confirm that our indicators suffer from spatial

[21] More information on the notion of spatial dependence can be found in Lesage and Pace (2009).

dependence, observation across the different spatial units is not fully independent and warrants further investigation.

Table 3. Moran I (by *barri*)

Source: Own database; Calculus: Authors

Variable	Moran's I	p-value
Diversity index by continent	4.3171	0.0000
Diversity index by country	2.5129	0.0060
Polarization index	3.572	0.0002
Relative distance, RD (language)	6.490	0.0000
Relative distance, RD (religion)	6.168	0.0000
Relative distance, RD (genetic)	6.242	0.0000
Total share of immigrants	5.499	0.0000
Share of African immigrants	4.769	0.0000
Share of American immigrants	1.879	0.0301
Share of Asian immigrants	4.505	0.0000
Share of European immigrants	10.137	0.0000

5. Empirical strategy and estimation results

In the light of the contributions in the literature, our framework of analysis grants a lot to the idea to select covariates for our analysis by looking at possible *pull* factors for immigrants in destination places. The quantitative analysis that we perform in this section aims at disentangling the determinants that could impact the different indicators, approximating any possible interaction between natives and immigrants. In particular, we focus on a series of determinants at the level of *barris* to take into account selected socioeconomic features of one of the most specific spatial units in Barcelona that are expected to be factors of attractiveness to immigrants. From that perspective, we include the *index of available income* of households in a spatial unit (i.e., the *barri*), a variable expected to embed the socioeconomic status of a place, which influences the level of rents, for instance, and shapes the group of people suitable to establishing residence there, as discussed in Rosenthal and Ross (2015). Another dimension that we take into account is the incoming immigrants' proximity to work. Most immigrants, especially ones from Latin American and European countries, find jobs in the services sector, mostly in childcare or geriatric care. To grasp that dimension, in our estimation we include shares of the population that approximate those two categories of individuals in each *barri* (i.e., *share population 0–14* and *share population 65 or more*). By the same token, immigrants might increase the probability of being employed in any type of household services whenever there is a higher proportion of people in each household who work. We take into account that dimension by including the *average number of employees per household*. A final dimension that we consider is the effective probability of any interaction between natives and immigrants in the same spatial unit. We approximate this dimension with the *population density* at the level of *barri*, calculated as the number of individuals per hectare, as well as the *share of women* in the population. According to evidence in the literature: women are more prone to bridge the gap with immigrants and indirectly fuel social cohesion, as shown in the United States (Blau, 2015).

Therefore, the baseline equation to be estimated is:

$$Ind_{migr_{s,t}} = \beta_0 + \beta_1 Controls_{s,t-1} + \gamma_s + \delta_t + \varepsilon_{s,t} \qquad (1)$$

In Equation 1, the dependent variable is (alternatively) one of the different indicators discussed in Section 3 that emphasize the relationship between immigrants and natives, whereas our control variables are the selected indicators (i.e., *index of available income*, *share population 0–14*, *share population 65 or more*, *population density*, and *share of women*). The equation also takes into account fixed effects at the *barri* level (γ_s , i.e., 73 spatial units) and time-fixed effects (δ_t). As for the time span covered by our sample, the full data set covers the period 2008–2020. However, we drop 2 years due to data inconsistencies and missing observations to gather a final balanced panel data for the period 2010-2020 (i.e., 803 observations). To avoid the bias generated by the potential double causality between dependent variables and covariates, all of the covariates are lagged to one period.

Table 4 shows the results of estimating Equation (1), in which we do not explicitly consider the spatial dimension of the distribution of observations. Those estimations furnish two important pieces of information. On average, our results seem to point out that higher income leads to lower diversification. This effect could be capturing the fact that higher income in *barris* seem to be concentrating mostly natives and/or Europeans, while pushing other migrants, particularly Africans and Asians, to the peripheral areas. This latter effect could explain the positive (direct) effect of the index of income on polarization. Migration indices seem confirming this reading: high-income persons are more prone to locate in specific *barris* of the city, irrespective of their ethnic community; this effect is particularly sizable in the case of (high-income) Europeans that seems to show a high propensity to choose the same locations of (high-income) natives.

Another important result is the impact of gender and age on diversity, in particular referring to Americans. The effects of the two extreme age cohorts contrast without offering a unified reading of the different effects. The gender dimension contributes to increase the index of diversity. In terms of size, for the selected group of migrants, for women migrating from Asian and European countries, we observe a positive association with a higher share of correspondent group migrants in the different *barris* of Barcelona. Instead, the reverse holds in the case of the groups of Americans. This outcome is likely to be driven by the sub-group of Latin American migrants. Women from Latin America are often hired for home-service jobs, mostly for their high level of language proximity with natives. If so, it is also likely that they might decide to live closer to their workplaces rather than clustering in the *barris* where other Latin American immigrants concentrate. Beyond that, population density in the *barris* clearly affects interaction between people and brings about either an increase in the cultural cleavage or a decreased share of immigrants in each *barri*. That result relates to the positive impact that the mean number of employees in a household has on the share of immigrants as well, both overall and at the ethnic level.[22]

[22] An increase in the number of workers in each household raises the need to outsource some household services, which accommodates the fact that various service tasks can be performed by immigrants (e.g., childcare).

Table 4. Panel estimations

VARIABLES	**Diversity index (Country)**	**Polarization index (Country)**	**Linguistic distance (Country)**	**Genetic distance (Country)**	**Religious distance (Country)**	**Share total (Immigrants)**	**Share African (Immigrants)**	**Share American (Immigrants)**	**Share Asian (Immigrants)**	**Share European (Immigrants)**
Index of available income	-0.0100**	0.0213**	-0.0423***	-0.00627***	-0.0306***	-0.0522***	-0.00320	-0.0125**	-0.0106**	-0.0254***
	(0.00428)	(0.00895)	(0.00916)	(0.00158)	(0.00692)	(0.0121)	(0.00231)	(0.00507)	(0.00490)	(0.00524)
Share population 0-14	-0.0278	0.0535	0.121	0.0316	0.0938	0.147	0.0512	0.0480	0.0341	0.0126
	(0.0614)	(0.128)	(0.131)	(0.0227)	(0.0992)	(0.173)	(0.0331)	(0.0727)	(0.0703)	(0.0752)
Share population 65 or more	-0.0748**	0.180**	-0.0404	-0.0145	-0.0412	-0.112	-0.0331*	-0.109***	-0.0191	0.0489
	(0.0348)	(0.0728)	(0.0747)	(0.0129)	(0.0564)	(0.0982)	(0.0188)	(0.0412)	(0.0398)	(0.0426)
Share of woman	0.0953***	-0.181***	0.430***	0.0119	0.334***	0.417***	0.0217	-0.0673*	0.237***	0.223***
	(0.0295)	(0.0617)	(0.0631)	(0.0109)	(0.0477)	(0.0832)	(0.0159)	(0.0349)	(0.0338)	(0.0361)
Population density	0.0004***	-0.0006***	-0.0009***	-5.18e-05**	-0.0008***	-0.0013***	-8.36e-06	-0.0003***	-0.0007***	-0.0003***
	(6.13e-05)	(0.000128)	(0.000131)	(2.26e-05)	(9.90e-05)	(0.000173)	(3.31e-05)	(7.26e-05)	(7.02e-05)	(7.50e-05)
Average number of employees per household	0.00454	0.00680	0.0997***	0.00942***	0.0759***	0.142***	0.0122***	0.0398***	0.0606***	0.0286***
	(0.00513)	(0.0107)	(0.0110)	(0.00189)	(0.00828)	(0.0145)	(0.00277)	(0.00607)	(0.00587)	(0.00628)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial fixed effects (*Barri*)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803	803	803	803	803
Number of *Barris*	73	73	73	73	73	73	73	73	73	73
Adj-R-squared	0.172	0.244	0.430	0.261	0.446	0.417	0.078	0.528	0.376	0.401
AIC	-5186.8	-4002	-3968	-6789.6	-4418.6	-3522.2	-6178.4	-4915.9	-4970.5	-4862.7
BIC	-5107.1	-3922.3	-3888.3	-6709.9	-4338.9	-3442.5	-6098.7	-4836.2	-4890.8	-4783

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

However, it is relevant to explicitly take into account in our setting the condition that nurtures the likelihood that citizens interact. In this respect, we add a spatial layer to our estimations by augmenting the specification of Equation (1). According to Elhorst (2014), there are two principal spatial models that embed two visions of the spatial dependence (and, hence, possible interaction) of observations.[23] One is the spatial lag X (SLX) model, a linear regression model extended to include explanatory variables observed on neighboring cross-sectional units in order to capture potential (spatial) spillover effects. In other words, an SLX model includes only exogenous spatial interaction effects. By contrast, the spatial Durbin model (SDM) accounts for endogenous spatial interaction effects. In the SDM specification, we take into account the spatially lagged values of all covariates jointly with the one of the dependent variables. The added value of such a spatial econometric model is the possibility of quantifying the effects of not only the selected covariates on the dependent variable in the same spatial unit s (i.e., direct effects) but also ones stemming from the values of the same covariates, along with the dependent variable in the case of the SDM, on the value of the dependent variable in s (i.e., indirect effects).

In spatial models, a critical choice is defining the proximity of the different spatial units to be included in the regression. The degree of proximity passes through the definition of a spatial weight matrix **W** for a spatial unit s. Although there are multiple definitions for that matrix, the most common is as a normalized adjacency matrix. The elements of the diagonal take the value of 0, whereas the elements of each row detecting the neighboring spatial units of unit s equal 1. [24] For our estimations, we follow the common practice in the literature and define **W** in a way to detect the spatial units bordering unit s.

Referring to the baseline Equation 1, in our setting an SLX specification of our model is presented in Equation 2:

$$Ind_{migr_{s,t}} = \beta_0 + \beta_1 Controls_{s,t-1} + \theta \boldsymbol{W} Controls_{s,t-1} + \gamma_s + \delta_t + \varepsilon_{s,t} \qquad (2)$$

in which β_1 represents the direct effects of our covariates on the dependent variables in the spatial unit s, and θ represent the effects of the covariates in the bordering spatial units of s on the dependent variable in the spatial unit s (i.e., indirect or spillover effects).

By contrast, in the same framework, the specification for the SDM is presented in Equation (3):

[23] Test's results about the most preferred spatial specification are presented in the Appendix (Table A.1).

[24] That weighting operation can be interpreted as an averaging of neighboring values

$$Ind_{migr_{s,t}} = \beta_0 + \beta_1 Controls_{s,t-1} + \rho \boldsymbol{W} Ind_{migr_{s,t}} + \theta \boldsymbol{W} Controls_{s,t-1} + \gamma_s + \delta_t + \varepsilon_{s,t} \quad (3)$$

In the case of the SDM, we cannot directly deduce the direct and indirect effects from the estimation due to the presence of ρ, even if they have the same meaning. To provide that type of information, we need to compute the marginal effects.

In Tables 5–14, we present the marginal effects in order to directly perform the interpretation of the results.[25] In all of our settings, there is no striking difference between the results of the two specifications, and their predictive capacity is quite comparable.

Table 5. Spatial Estimations: diversity index by country
Spatial units: *barris*.
Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0147*** (0.0052)	0.0104 (0.0079)	-0.0044 (0.0065)	-0.0149*** (0.0052)	0.0106 (0.0079)	-0.0043 (0.0064)
Share population 0-14	-0.0286 (0.0605)	-0.0492 (0.1670)	-0.0778 (0.1791)	-0.0284 (0.0605)	-0.0433 (0.1645)	-0.0717 (0.1757)
Share population 65 or more	-0.0735** (0.0344)	0.0867 (0.0902)	0.0132 (0.0988)	-0.0734** (0.0343)	0.0874 (0.0884)	0.0140 (0.0965)
Share of woman	0.0892** (0.0368)	0.0172 (0.0514)	0.1064** (0.0410)	0.0898** (0.0369)	0.0144 (0.0515)	0.1042** (0.0405)
Population density	0.0004*** (0.0001)	0.0003** (0.0002)	0.0007*** (0.0002)	0.0004*** (0.0001)	0.0003** (0.0002)	0.0007*** (0.0002)
Average number of employees per household	0.0046 (0.0051)	-0.0179 (0.0136)	-0.0133 (0.0151)	0.0046 (0.0051)	-0.0176 (0.0133)	-0.0130 (0.0147)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-4641.2			-4639.3	
BIC		-4533.3			-4526.8	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

[25] Raw estimations are available upon request.

Table 6. Spatial Estimations: polarization index by country
Spatial units: *barris*.
Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	0.0324***	-0.0224	0.0101	0.0313***	-0.0196	0.0117
	(0.0107)	(0.0165)	(0.0136)	(0.0105)	(0.0176)	(0.0153)
Share population 0-14	0.0620	0.0964	0.1585	0.0644	0.1454	0.2098
	(0.1255)	(0.3464)	(0.3716)	(0.1258)	(0.3840)	(0.4179)
Share population 65 or more	0.1746**	-0.2250	-0.0504	0.1780**	-0.2153	-0.0372
	(0.0713)	(0.1871)	(0.2050)	(0.0716)	(0.2073)	(0.2300)
Share of woman	-0.1294*	-0.1239	-0.2534***	-0.1243*	-0.1575	-0.2817***
	(0.0762)	(0.1066)	(0.0851)	(0.0749)	(0.1145)	(0.0971)
Population density	-0.0006***	-0.0011***	-0.0017***	-0.0006***	-0.0011***	-0.0016***
	(0.0001)	(0.0004)	(0.0004)	(0.0001)	(0.0004)	(0.0004)
Average number of employees per household	0.0066	0.0613**	0.0679**	0.0069	0.0663**	0.0732**
	(0.0106)	(0.0281)	(0.0313)	(0.0107)	(0.0314)	(0.0352)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-3576			-3577.1	
BIC		-3468.2			-3464.6	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Concerning the index of diversity (Table 5), the direct effect of the average level of income at the *barri* level on the index of diversity is confirmed in the case of the country index, supporting our argument that higher income level *barris* are hosting selected group of migrants that mostly assimilate with natives.

As for the age composition of the population, the most robust statistically significant effects appear in the case of the diversity index by country. The concentration of older people is associated with a drop of the index of diversity since they are likely to mostly interact with the group(s) of migrants more involved in elderly assistance, whereas younger ones are not showing a significant effect. Last, population density again registers a negative effect on the index of diversity as well as on the polarization index. This effect might be capturing potential congestion effects in dense neighborhoods such to limit the increase of the size of the different communities located there, likely to happen no just due to higher migration inflows but also due to massification in certain areas.

Considering the migration shares—that is, the ones referring to the share of migrants over natives—the results of spatial estimations are not especially conclusive (Tables 7–12).

A feature common to various estimations is the (direct) positive effect of the number of employees in each *barri* on attracting immigrants (Borja, 1995). Again, the mechanism supporting that effect is clearly a situation in which natives in the job market make it possible for immigrants to replace them in some tasks.

The (direct) effect stemming from the size of the local population is negative and statistically significant. Once more, pointing to potential setbacks coming from more densification in each *barri*.

Again, the relative language proximity with natives increases the share of immigrants in each *barrio.*

Interesting findings refer to our set of estimations for American migrants. We observe a negative direct effect and a positive one on both, the share of elderly and the share of women. The evidence suggest that American migration chose to locate in neighboring areas where there is higher concentration of women and elderly population, supporting the argument that they are choosing to reside in areas close to their workplace. Again, that result can be interpreted from a labor market perspective and according to the theory of substitution between natives and immigrants. It is reasonable to think that women and the elderly are quite likely to count on immigrants for childcare or housing services and hence this effect is likely to attract more immigrants in places nearby where the concentration of women and elderly is higher and it achieve a minimum threshold size, something that is captured by the consistent statistical significance of spillovers effects.

Last, referring to composition by age, positive effects towards a reduction of the index of diversity (or the increase of the size for a selected group of migrants) are usually direct effects inside each spatial unit. The demand for care services in a *barri* increases the attractiveness for immigrants to locate there, while indirect effects become negative. Once more, the location of the demand for care services promotes the tendency for migrants to locate in their proximity.

Table 7. Spatial Estimations: Total immigration rate
Spatial units: *barris*.
Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0356** (0.0145)	-0.0369* (0.0223)	-0.0725*** (0.0184)	-0.0347** (0.0139)	-0.0451* (0.0258)	-0.0798*** (0.0237)
Share population 0-14	0.1073 (0.1698)	-0.4755 (0.4686)	-0.3682 (0.5027)	0.0899 (0.1707)	-0.6552 (0.5880)	-0.5653 (0.6475)
Share population 65 or more	-0.0917 (0.0964)	-0.0303 (0.2532)	-0.1220 (0.2774)	-0.0863 (0.0973)	0.0241 (0.3178)	-0.0621 (0.3558)
Share of woman	0.2187** (0.1031)	0.4633*** (0.1443)	0.6819*** (0.1152)	0.1786* (0.0993)	0.6859*** (0.1784)	0.8645*** (0.1598)
Population density	-0.0013*** (0.0002)	-0.0005 (0.0005)	-0.0018*** (0.0005)	-0.0013*** (0.0002)	-0.0006 (0.0006)	-0.0019*** (0.0007)
Average number of employees per household	0.1430*** (0.0143)	0.0224 (0.0381)	0.1655*** (0.0423)	0.1440*** (0.0145)	0.0135 (0.0480)	0.1575*** (0.0542)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-3134.6			-3147.1	
BIC		-3026.7			-3034.6	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Table 8. Spatial Estimations: Share African immigrants

Spatial units: *barris*.

Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0031 (0.0028)	0.0005 (0.0043)	-0.0026 (0.0035)	-0.0036 (0.0029)	0.0011 (0.0036)	-0.0025 (0.0023)
Share population 0-14	0.0453 (0.0325)	-0.0847 (0.0897)	-0.0394 (0.0962)	0.0474 (0.0327)	-0.0555 (0.0646)	-0.0081 (0.0622)
Share population 65 or more	-0.0262 (0.0185)	0.1378*** (0.0485)	0.1115** (0.0531)	-0.0265 (0.0184)	0.0992*** (0.0349)	0.0726** (0.0346)
Share of woman	-0.0050 (0.0197)	0.0701** (0.0276)	0.0651*** (0.0220)	0.0021 (0.0209)	0.0473* (0.0242)	0.0493*** (0.0143)
Population density	-0.00002 (0.0000)	-0.00001 (0.0001)	-0.00002 (0.0001)	-0.00002 (0.0000)	0.00001 (0.0001)	-0.00001 (0.0001)
Average number of employees per household	0.0121*** (0.0027)	-0.0064 (0.0073)	0.0057 (0.0081)	0.0117*** (0.0027)	-0.0049 (0.0052)	0.0069 (0.0052)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-5548.7			-5584.3	
BIC		-5440.9			-5471.8	

Constant included *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Table 9. Spatial Estimations: Share American immigrants

Spatial units: *barris*.

Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0074 (0.0061)	-0.0106 (0.0093)	-0.0180** (0.0077)	-0.0075 (0.0062)	-0.0097 (0.0085)	-0.0173*** (0.0063)
Share population 0-14	0.0281 (0.0709)	-0.4267** (0.1958)	-0.3986* (0.2100)	0.0315 (0.0708)	-0.3507** (0.1688)	-0.3193* (0.1747)
Share population 65 or more	-0.0935** (0.0403)	0.2249** (0.1058)	0.1314 (0.1159)	-0.0998** (0.0401)	0.2064** (0.0904)	0.1066 (0.0960)
Share of woman	-0.1551*** (0.0431)	0.2204*** (0.0603)	0.0652 (0.0481)	-0.1453*** (0.0442)	0.1915*** (0.0565)	0.0462 (0.0400)
Population density	-0.0003*** (0.0001)	-0.0001 (0.0002)	-0.0004* (0.0002)	-0.0003*** (0.0001)	-0.0001 (0.0002)	-0.0004** (0.0002)
Average number of employees per household	0.0396*** (0.0060)	-0.0077 (0.0159)	0.0319* (0.0177)	0.0391*** (0.0059)	-0.0051 (0.0135)	0.0340** (0.0146)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-4409			-4416.7	
BIC		-4301.1			-4304.2	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Table 10. Spatial Estimations: Share Asian immigrants
Spatial units: *barris*.
Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0109* (0.0059)	0.0019 (0.0091)	-0.0090 (0.0075)	-0.0107* (0.0058)	0.0013 (0.0096)	-0.0094 (0.0082)
Share population 0-14	0.0264 (0.0695)	-0.0104 (0.1917)	0.0160 (0.2057)	0.0252 (0.0696)	-0.0141 (0.2074)	0.0111 (0.2252)
Share population 65 or more	-0.0104 (0.0395)	0.1533 (0.1036)	0.1429 (0.1135)	-0.0104 (0.0396)	0.1666 (0.1127)	0.1562 (0.1247)
Share of woman	0.2164*** (0.0422)	0.0566 (0.0590)	0.2730*** (0.0471)	0.2102*** (0.0418)	0.0816 (0.0646)	0.2918*** (0.0537)
Population density	-0.0007*** (0.0001)	-0.0002 (0.0002)	-0.0009*** (0.0002)	-0.0007*** (0.0001)	-0.0002 (0.0002)	-0.0009*** (0.0002)
Average number of employees per household	0.0599*** (0.0059)	-0.0144 (0.0156)	0.0455*** (0.0173)	0.0600*** (0.0059)	-0.0165 (0.0170)	0.0435** (0.0190)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-4439.4			-4439.3	
BIC		-4331.6			-4326.7	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Table 11. Spatial Estimations: Share European immigrants
Spatial units: *barris*.
Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0138** (0.0061)	-0.0283*** (0.0094)	-0.0421*** (0.0078)	-0.0146*** (0.0049)	-0.0612*** (0.0199)	-0.0758*** (0.0207)
Share population 0-14	0.0062 (0.0719)	0.0464 (0.1985)	0.0526 (0.2130)	-0.0085 (0.0739)	-0.0056 (0.4919)	-0.0140 (0.5414)
Share population 65 or more	0.0388 (0.0409)	-0.5393*** (0.1072)	-0.5005*** (0.1175)	0.0247 (0.0423)	-0.9629*** (0.2793)	-0.9382*** (0.3080)
Share of woman	0.1602*** (0.0437)	0.1157* (0.0611)	0.2759*** (0.0488)	0.1474*** (0.0352)	0.6436*** (0.1476)	0.7909*** (0.1532)
Population density	-0.0002*** (0.0001)	-0.0003 (0.0002)	-0.0005** (0.0002)	-0.0002*** (0.0001)	-0.0006 (0.0005)	-0.0009 (0.0006)
Average number of employees per household	0.0308*** (0.0061)	0.0509*** (0.0161)	0.0817*** (0.0179)	0.0311*** (0.0064)	0.0756* (0.0411)	0.1067** (0.0457)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-4388.7			-4602.9	
BIC		-4280.9			-4490.3	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Finally, Tables 12-14 present the results of spatial estimations referring to linguistic, genetic and religious distance. Linguistic and religious distances seem to gain relevance from the introduction of the geographic dimension in the estimation: both direct and indirect spillovers effect are often significant. The negative effect stemming from the index of income both in the case of linguistic and religious distance is likely to point out the fact that the high income *barris* are pushing away those migrants who are further away in terms of language and religion with respect to natives. And this is happening directly in the selected *barri* as well as in neighboring ones. This result implicitly means that natives show clear preferences for not locating in neighborhoods where the other citizens (in the same and surrounding neighborhoods) do not share their language or religion. Genetic distance also registers a similar direct effect for income, but indirect effects are not significant. Overall, linguistic, and religious distance seem to be the strongest factors that tend to push migrants to peripheral areas.

Another interesting feature stemming from the estimations of these indicators refer to the gender dimension. The positive and strong direct and indirect effects of the estimates associated to this covariate confirms that the likelihood of interaction with natives (by jobs like childcare or homecare services), and above all the communication skills, favors the clustering of migrants close to natives exhibiting proximity in terms of language and religion in both a *barri* and the surrounding ones.

Table 12. Spatial Estimations: Linguistic distance
Spatial units: *barris*.
Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0318*** (0.0119)	-0.0340* (0.0184)	-0.0657*** (0.0151)	-0.0305*** (0.0109)	-0.0521** (0.0250)	-0.0826*** (0.0243)
Share population 0-14	0.2286 (0.2091)	-0.4130 (0.5804)	-0.1845 (0.6232)	0.1756 (0.2119)	-0.8136 (0.8960)	-0.6380 (0.9953)
Share population 65 or more	-0.0232 (0.0766)	-0.2390 (0.2004)	-0.2622 (0.2195)	-0.0225 (0.0779)	-0.2191 (0.3097)	-0.2416 (0.3484)
Share of woman	0.3093*** (0.0815)	0.2985*** (0.1148)	0.6078*** (0.0913)	0.2629*** (0.0747)	0.6804*** (0.1711)	0.9433*** (0.1646)
Population density	-0.0009*** (0.0001)	-0.0006 (0.0004)	-0.0015*** (0.0004)	-0.0009*** (0.0001)	-0.0009 (0.0006)	-0.0018*** (0.0007)
Average number of employees per household	0.0981*** (0.0114)	0.0200 (0.0304)	0.1181*** (0.0338)	0.0982*** (0.0117)	0.0028 (0.0474)	0.1010* (0.0537)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-3540.9			-3587.1	
BIC		-3433.1			-3474.6	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Table 13. Spatial Estimations: Genetic distance

Spatial units: *barris*.

Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0053** (0.0021)	-0.0041 (0.0032)	-0.0093*** (0.0026)	-0.0052*** (0.0020)	-0.0048 (0.0035)	-0.0100*** (0.0031)
Share population 0-14	0.0503 (0.0361)	-0.1958* (0.1001)	-0.1455 (0.1075)	0.0463 (0.0362)	-0.2412** (0.1195)	-0.1949 (0.1310)
Share population 65 or more	-0.0120 (0.0132)	-0.0175 (0.0346)	-0.0295 (0.0379)	-0.0115 (0.0133)	-0.0137 (0.0408)	-0.0252 (0.0455)
Share of woman	-0.0055 (0.0141)	0.0466** (0.0198)	0.0411*** (0.0157)	-0.0084 (0.0137)	0.0591*** (0.0223)	0.0507*** (0.0194)
Population density	-0.0001** (0.0000)	-0.00004 (0.0001)	-0.0001 (0.0001)	-0.0001** (0.0000)	-0.00004 (0.0001)	-0.0001 (0.0001)
Average number of employees per household	0.0088*** (0.0020)	0.0019 (0.0052)	0.0108* (0.0058)	0.0088*** (0.0020)	0.0006 (0.0062)	0.0094 (0.0070)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-6097.9			-6102.9	
BIC		-5990.1			-5990.3	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

Table 14. Spatial Estimations: Religious distance
Spatial units: *barris*.
Method of estimation: SLX: nonlinear OLS; SDM: ML

	SLX			SDM		
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total
Index of available income	-0.0241*** (0.0090)	-0.0206 (0.0139)	-0.0447*** (0.0114)	-0.0232*** (0.0084)	-0.0305* (0.0177)	-0.0537*** (0.0168)
Share population 0-14	0.1762 (0.1582)	-0.4143 (0.4392)	-0.2380 (0.4716)	0.1434 (0.1598)	-0.6617 (0.6205)	-0.5183 (0.6879)
Share population 65 or more	-0.0260 (0.0579)	-0.1024 (0.1516)	-0.1284 (0.1661)	-0.0246 (0.0587)	-0.0638 (0.2144)	-0.0884 (0.2410)
Share of woman	0.2517*** (0.0617)	0.2105** (0.0868)	0.4621*** (0.0691)	0.2200*** (0.0578)	0.4339*** (0.1199)	0.6539*** (0.1122)
Population density	-0.0008*** (0.0001)	-0.0004 (0.0003)	-0.0013*** (0.0003)	-0.0008*** (0.0001)	-0.0006 (0.0004)	-0.0014*** (0.0005)
Average number of employees per household	0.0740*** (0.0086)	0.0093 (0.0230)	0.0833*** (0.0256)	0.0740*** (0.0088)	-0.0035 (0.0328)	0.0705* (0.0372)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	803	803	803	803	803	803
Number of groups	73	73	73	73	73	73
AIC		-3946.7			-3974.8	
BIC		-3838.9			-3862.3	

Constant included. *Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1*

6. Time trend

Once assessed the relative importance of income, language and religion distance in shaping the distribution of migrants in the city, we propose an extension of our baseline framework of analysis in the case of the index of diversity by country, polarization, linguistic, religion and genetic distance. We propose to analyze the evolution over time of the relative importance of the index of income (in destination *barris*) and the selected indicators (Figure 14). In order to understand the possible changes of the relative importance of the index of income in shaping the distribution over time of the previous indicators, we retrieve the results in Table 5, 6, 12-14 and we plot the estimated coefficient year by year from 2011 to 2020.[26]

Figure 14. Time effects, RDF estimated coefficients.

Diversity index

Polarization index

Genetic distance

Linguistic distance

Religious distance

[26] The full estimations results are available upon request. Plots in Figure 8 refer to marginal effects in spatial models; results for panel estimations are similar and, once more, are available upon request.

The index of income is becoming relevant in shaping the polarization indicator and the linguistic distance. In the last year, the level of income seems contributing in increasing the polarization index (high income persons clusters in specific location) and, the same time, it becomes less relevant for the linguistic distance: high-income persons have the possibility to get educated and, hence, increase the learning of language that favor the communication between natives and immigrants and, de facto, eliminating the assimilation obstacles entailed by the linguistic distance. However, this effect is observed from 2014, and it can be associated with the variation of migration inflows from the Americas and their distribution over space in the city. The sudden increase in American migration, after the decreasing trend before 2014, could have fueled more polarization of African and Asian migrants in marginal areas. The inflow of Latin Americans, and subsequent location in neighboring areas where natives reside, given their linguistic and cultural proximity, could have shaped a more uneven distribution of the population across the city, whose effects become tangible from 2018. European migration also seemed to contribute to reshaping the distribution of ethnic communities of migrants in Barcelona. European experienced a big boost in entries (larger than that of Americans) after 2014, and they show a tendency to settle in high-income locations, and, hence, generating a displacement of the other community of migrants. The group of Europeans is quite heterogeneous, but they share similar cultural and religious traits with natives; and also, the linguistic distance is not a true problem because they show a certain facility – given their linguistic background- in learning the language spoken by natives in the host destination.

7. Conclusion

Our analysis allows for disentangling that, in Barcelona, the polarization trend is progressively decreasing over time whereas the diversity increased polarization having a clear pattern of distribution of migrants mostly driven by determinants like the index of income and the linguistic distance. Incoming migrants with high level of income and linguistic proximity with natives are likely to share the same neighborhoods of residence with natives.

Also, we assess the relevance of the spatial dimension and the effectiveness of spillover effects across spatial units—in our case, *barris* in Barcelona. Thus, it is relevant to consider the value of spatial dependence in supporting the implementation of coordinated policies across *barris* or other districts. Territorial coordination enables the achievement of mass or threshold levels of crucial factors (e.g., population density), which magnify the expected effects at a lower cost than can be achieved with decentralized policies.

The possibility of interaction between individuals belonging to different groups is a clear deterrent to discrimination and cultural cleavage in general. Any initiative that can facilitate the possibility of immigrant–native interaction is definitely welcome as a means to reduce the cultural divide in Barcelona.

Another important dimension of possibly favoring the assimilation of immigrants is the labor market. Although more investigation is clearly needed at that level,[27] some suggestions are obvious. There is an undeniable complementary effect between natives and immigrants. Immigrants are often called to replace natives in some tasks, mostly in the service sector and especially in childcare and geriatric care, when natives are active in the labor market. However, those types of tasks also seem to drive competition among women, particularly native ones, given the few skills generally required. Again, the mismatch between natives and immigrants occurs, and the solution could be linked to a plan to fuel the differentiation of tasks that each group can perform and from which all of society can benefit.

Last, education still turns to be relevant in defining possible strategies to favor the migrant's integration in the host society given the relevance of the linguistic distance and income identified in our analysis. Our results emphasize that a higher level of income helps to reduce the perceived diversity between natives and immigrants. Individuals form such perceptions and beliefs based on several factors, including previous experience, family background, and level of education. Therefore, a deep reading of the results again stresses that the value of education is a primary factor of a higher degree of social cohesion in Barcelona. Thus, it is doubtlessly valuable to consider the possibility of enlarging the range of policies supporting accessibility to higher degree of education for all citizens. Still in this wake, the cultural dimension (represented by the language distance) is another important factor contribution to the reduction of the cultural cleavage. We identified that language proximity helps to favor the decrease of the index of diversity, above all in the last years. Put this result in perspective, it reinforces the idea that interaction and communication among

[27] From this perspective, when examining labor market issues, the analysis should be broadened to include a wider range of languages as proxies for linguistic distance, incorporating Catalan as well, given its central role in communication within service sectors like education and healthcare

members of the different communities helps to reinforce social cohesion and, in this sense, education can be an additional trigger to support the shrinking of the language distance.

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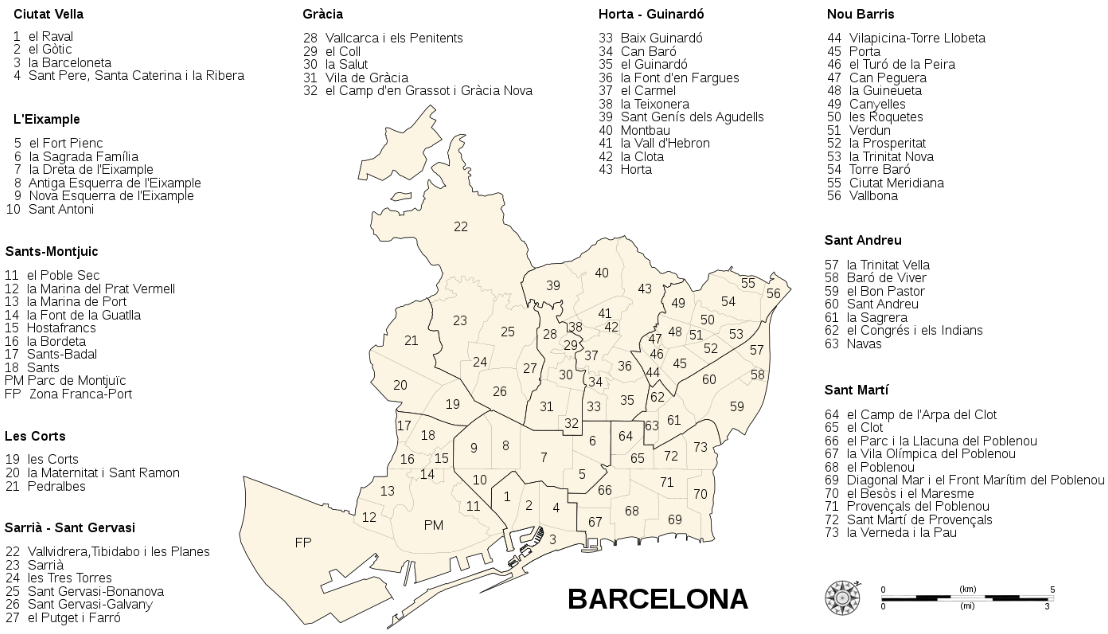
Appendix

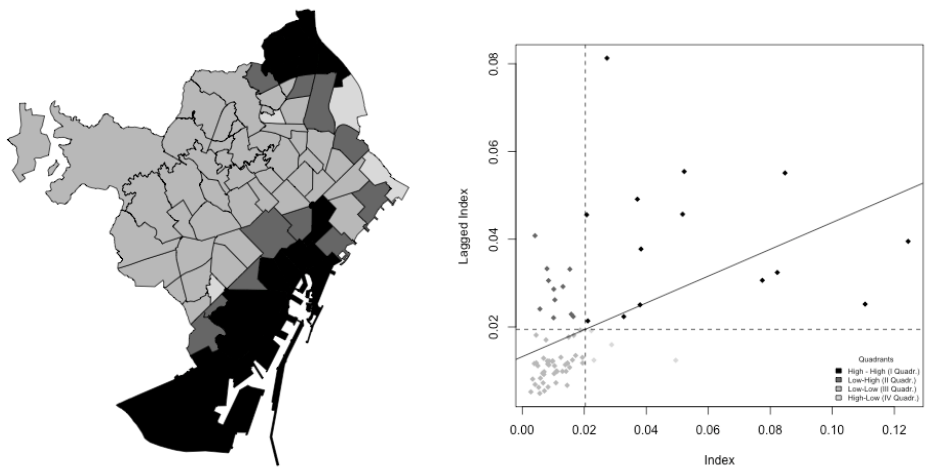
Map of Barcelona (districts and neighborhoods)



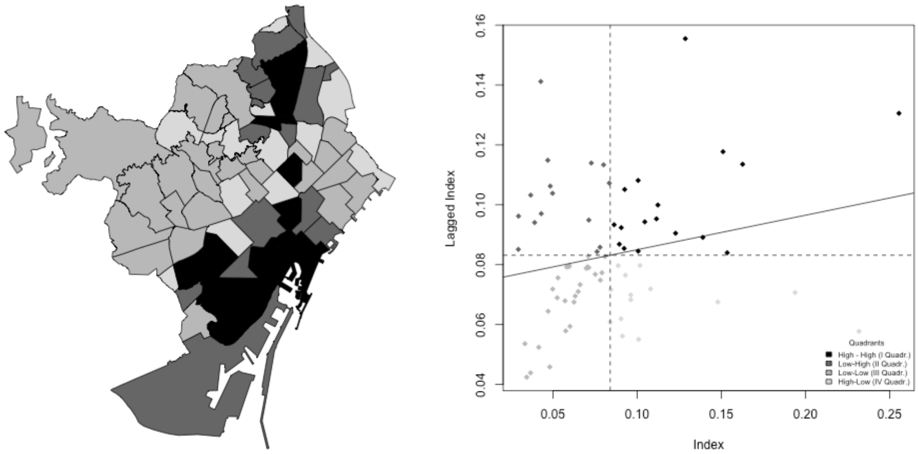
Source: Sémhur (2008); Free Art Licence; CC-BY-SA-3.0. Data: Ajuntament de Barcelona

Figure A.1 : LISA statistics (average values 2008-2020)

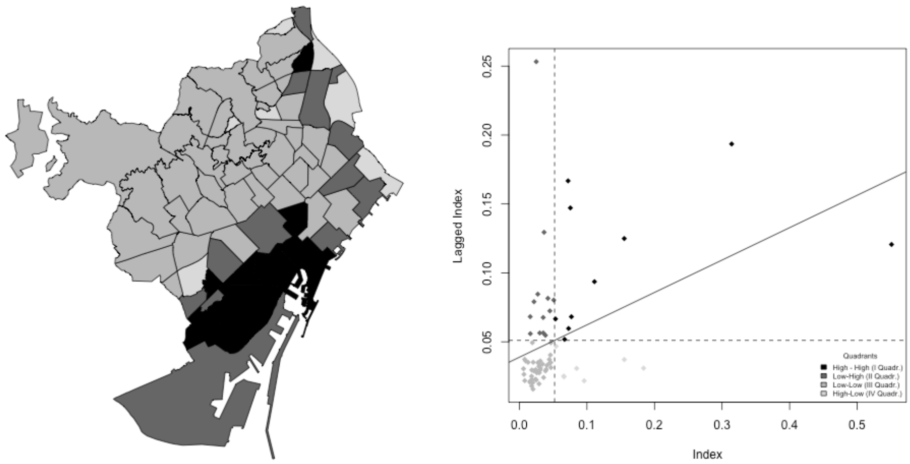
a) Africans



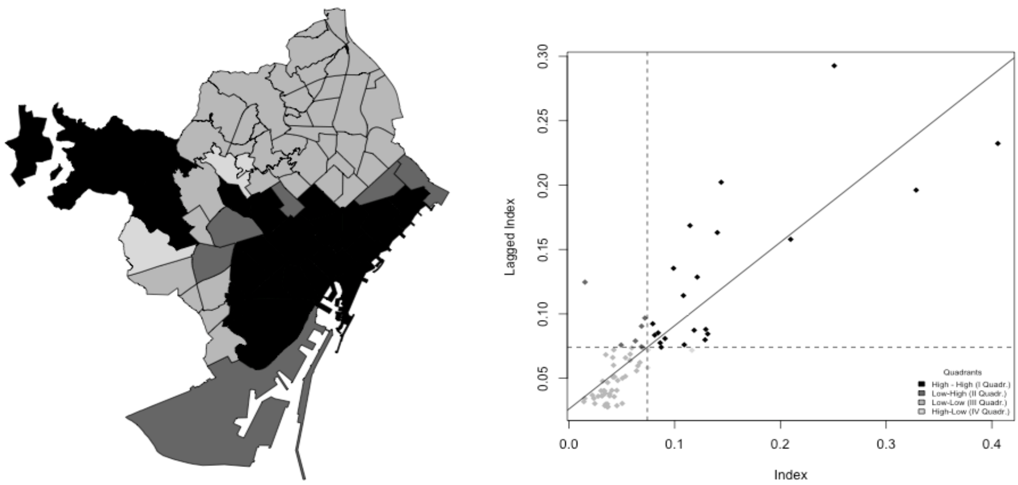
b) Americans



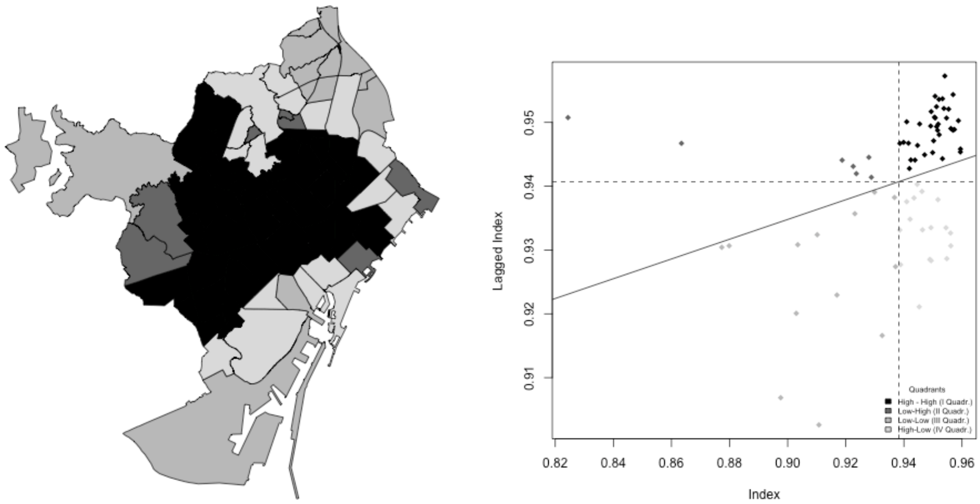
c) Asians



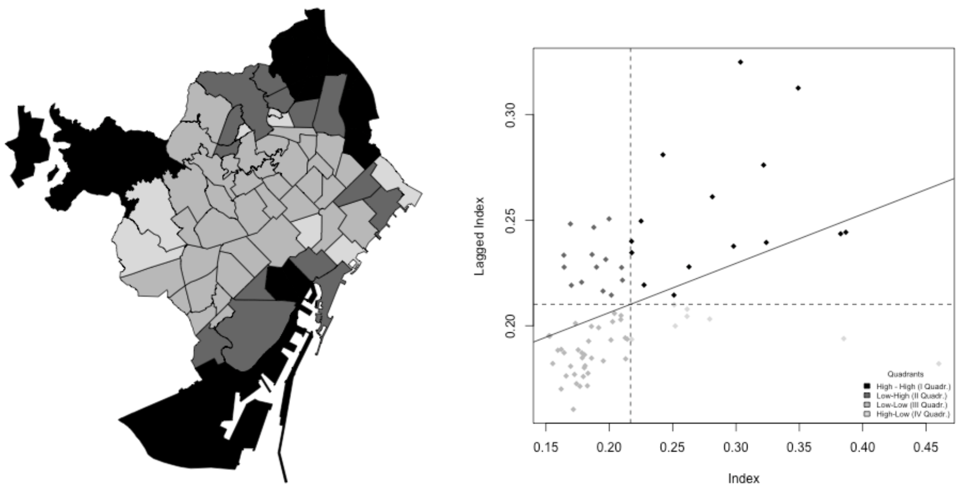
d) Europeans



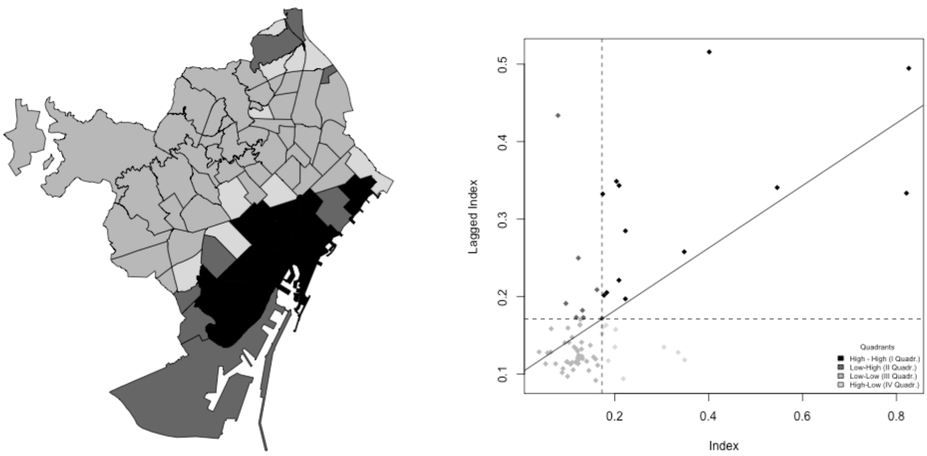
e) Diversity



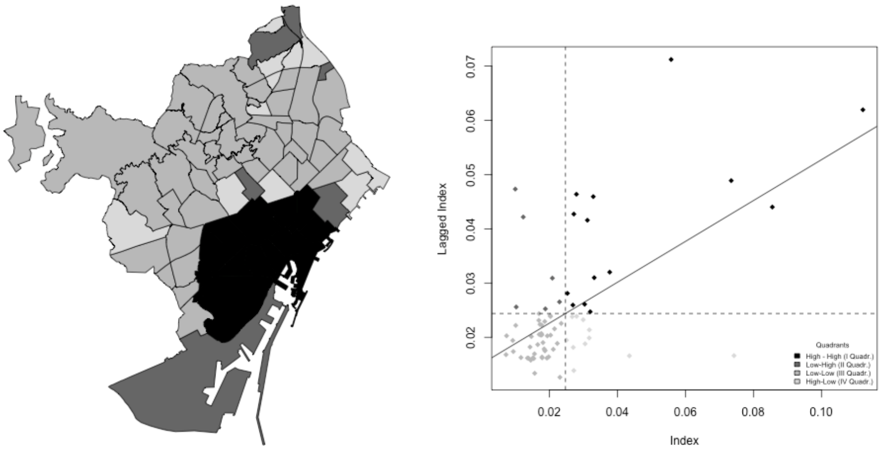
f) Polarization



g) Linguistic Distance



h) Genetic Distance



i) Religious distance

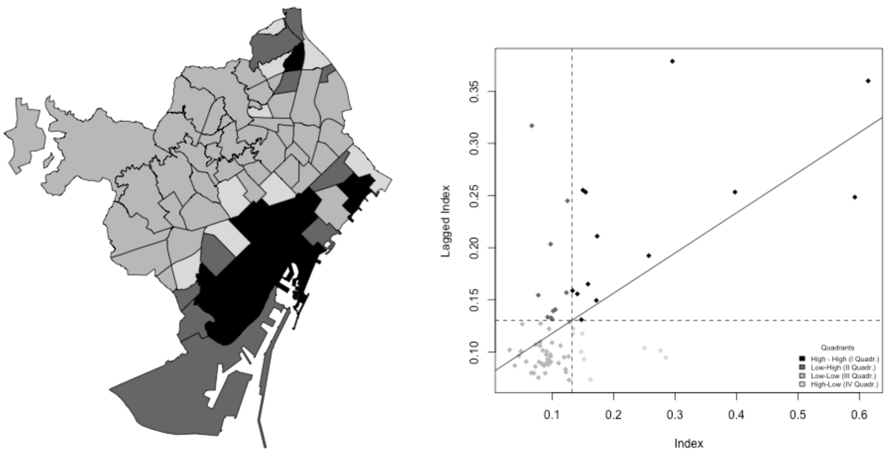


Table A.2 : Tests for the selection of the most suitable spatial model

Dependent variable	LR test Resticted model SDM		
	Log Likelihood (p-value)		
	SAR	SEM	SLX
Diversity index by continent	1774.29***	1765.57***	1749.34***
Diversity index by country	2347.01**	2347.21**	2354.45

*Statistical significance: *** 1%; **5%; * 10%*

The Lagrange tests confirm that the SDM model should be preferred to the SAR and SEM models, but it is not always the case for the SLX model. Therefore, we estimate the spatial models both by exploiting the SDM and SLX setting.