Residential Segregation in Europe: A Comparative Study of Spatial Segregation Patterns in Urban Areas across 30 Countries

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Abstract

Residential segregation can profoundly shape immigrant integration, access to opportunity, and inter-group relations. Yet we lack systematic evidence on how segregation levels vary across European cities and what structural factors drive these patterns. This study addresses two questions: (i) How does immigrant-native segregation vary across urban areas in Europe, and how much of this variation stems from local versus national contexts? (ii) Which urban and country-level characteristics are consistently associated with segregation?

Using harmonised 1×1 km grid-level data from the 2021 European census, we calculate spatially weighted Dissimilarity Indices for all 717 Functional Urban Areas (FUAs) across 30 countries. We combine these measures with rich data on housing, demographics, economy, education, and immigration policy. To identify robust correlates, we apply Specification Curve Analysis across 24,000 regression models.

Segregation is highest in Western and Northern Europe, but 40% of variation occurs within countries. At the urban level, higher segregation is linked to larger populations, lower densities, smaller immigrant shares, greater support for far-right parties, higher immigrant-native economic inequality, and lower homeownership rates. At the national level, economic inequality is negatively associated with segregation, while welfare spending, housing investment, and MIPEX scores show no consistent effects.

These findings offer the most comprehensive comparative assessment of immigrant segregation across Europe to date, revealing how structural conditions shape spatial integration – and raising new questions about the urban and national contexts in which segregation emerges.

Keywords: Residential Segregation, Europe, Immigrants, Comparative

Introduction and Background

Introduction

Residential segregation has significant implications for the opportunities available to minority groups and for broader social cohesion. For instance, restricts contact opportunities in neighbourhoods and the diversity of other settings such as schools, community organizations, and public amenities (Boterman and Musterd 2016; De La Prada and Small 2024; Wiertz 2016), and can substantially constrain access to resources and opportunities (Chetty, Hendren, and Katz 2016; Sharkey and Faber 2014; Wodtke et al. 2023). A large body of research has documented patterns of racial residential segregation in the United States (Elbers 2024; Lee et al. 2008; Lichter, Parisi, and Taquino 2015; Logan 2012; Massey and Denton 1988; Roberto and Korver-Glenn 2021) and immigrant residential segregation in Europe (Benassi et al. 2020; Catney et al. 2023; Lichter, Parisi, and Ambinakudige 2019; Marcińczak et al. 2023; Musterd 2005; Rüttenauer 2022; Sleutjes, De Valk, and Ooijevaar 2018; Spierenburg, Van Cranenburgh, and Cats 2023; Teltemann, Dabrowski, and Windzio 2015).

Traditionally, research has focused on three key mechanisms – often referred to as the "big three": (i) preferences for living near in-group members (Bruch and Mare 2006; Crowder and South 2008; Krysan et al. 2009; Liebe, van Cranenburgh, and Chorus 2023), (ii) socio-economic disparities that lead to unequal housing budgets and sorting (Alba et al. 1999; Charles 2003; Lersch 2013), and (iii) discrimination in the housing market (Auspurg, Schneck, and Hinz 2019; Desmond and Wilmers 2019; Faber 2020; Heath and Di Stasio 2019; Quillian, Lee, and Honoré 2020; Rosen, Garboden, and Cossyleon 2021). While each mechanism likely has and important impact on segregation, recent work highlights their interdependence and the role of structural barriers that simultaneously shape preferences, economic inequalities, and discriminatory practices (Faber 2020; Krysan and Crowder 2017; Lichter et al. 2024; Parisi et al. 2025).

At the same time, several studies have examined city-level correlates of residential segregation (Benassi et al. 2020; Iceland and Scopilliti 2008; Kye and Halpern-Manners 2023; Lichter et al. 2024; Marcińczak et al. 2023; Parisi et al. 2025). This reflects the idea that segregation is not only driven by individual choices or market dynamics, but also by broader urban structures – such as housing policies, spatial layouts, and institutional arrangements – that vary across cities and can reinforce or mitigate segregation patterns. In the U.S., segregation tends to be higher in metropolitan areas with larger populations, higher minority shares, newer housing stock, and elevated poverty rates (Iceland and Scopilliti 2008; Kye and Halpern-Manners 2023; Lichter et al. 2024, 2015; Parisi et al. 2025). Comparative studies also underscore the urban–suburban divide, with minorities often over-represented in urban cores (Elbers 2024; Logan et al. 2023).

In Europe, comparative studies have similarly explored structural correlates of segregation (Andersson et al. 2018; Benassi et al. 2020, 2023; Johnston, Poulsen, and Forrest 2007; Koopmans 2010; Lichter et al. 2019; Marcińczak et al. 2023; Musterd 2005). These studies show, for example, that British cities tend to be more segregated than those in continental Europe, and that non-European immigrants are generally more segregated than European ones

(Benassi et al. 2020; Koopmans 2010; Marcińczak et al. 2023; Musterd 2005). Marcińczak et al. (2023) also finds that Southern European cities are less segregated at the macro scale than those in Central and Northern Europe – though this conclusion is based solely on data from Spain. Other findings suggest that segregation is positively associated with city size and immigrant share, and negatively associated with wealth and education levels (Benassi et al. 2020; Marcińczak et al. 2023).

Despite these important findings, previous studies focus on an overlapping selection of 5-8 countries, while many countries – particularly in Easter Europe – remain understudied in comparative research. Moreover, prior work has considered only a narrow set of macro-level correlates. The reasons for these constraints are mainly data limitations across Europe, including: (a) inconsistent definitions of immigrant status (e.g., citizenship vs. country of birth), (b) administrative differences in delineating urban areas, (c) a general lack of harmonised, cross-nationally comparable data across Europe, and (d) limited coverage of structural factors that may drive segregation. This gap in broad comparative research is particularly striking in light of the considerable diversity in urban characteristics and policy frameworks across Europe.

Our study does & contributions:

Our study addresses this gap by providing the most comprehensive analysis to date of immigrant residential segregation across European cities. We ask: (a) how does the level of immigrant segregation vary across Europe's urban areas?; and (b) which characteristics of urban areas and national contexts are associated with segregation levels? Out analysis covers all 717 Functional Urban Areas (FUAs) across 30 European countries – standardised spatial units that include city centres and surrounding commuting zones, enabling consistent comparisons across national contexts (roughly equivalent to metropolitan areas in the US). Using 1×1 km grid cell data from the 2021/22 European census, we calculate segregation indices for each FUA, capturing recent migration dynamics and ensuring harmonised definitions of urban areas and migration status – thereby significantly expanding the geographical scope of comparative studies.

We then link these segregation indices to a rich set of FUA- and country-level indicators drawn from multiple sources (XX), allowing us to jointly analyse the influence of local housing markets, national immigration policies, and broader socio-economic conditions. Given the large number of plausible ways to specify models and select explanatory variables, we employ Specification Curve Analysis, running 8,000 fixed-effects and 16,000 random-effects models. We thus identify which structural factors are consistently associated with segregation levels, thus advancing our understanding of how structural conditions are associated with immigrant separation and integration. In addition to its empirical contributions, our study provides a public dataset and interactive dashboard containing all segregation measures and macro-level indicators. This resource enables researchers, policymakers, and urban planners to explore the data, and re-use the segregation scores for further research questions.

Results

In our main results, we rely on the spatial dissimilarity index $\widetilde{D}$ as proposed by Reardon and O'Sullivan (2004). It measures "how different the composition of the individuals' local environments are, on average, from the composition of the population [in the FUA] as a whole" (Reardon and O'Sullivan 2004, see Methods section for more details); in other words, how unevenly immigrants and natives are distributed across space. To define the local environment, we use a 1 km radius, which roughly corresponds to institutional neighborhoods within which most individuals can reach essential amenities (Reardon et al. 2008). We begin with the comparison of segregation levels across FUAs (research question 1) and then analyse the correlates of segregation (research question 2).

To illustrate our measure of segregation, Figures 1 A) and B) depict the variation of the immigrant share per 1x1 km grid cell for the two FUAs of Leicester (United Kingdom) and Bonn (Germany). In Leicester, the proportion of immigrants varies strongly across grid cells, and grid cells with high proportions of immigrants are spatially clustered around the urban core, indicating substantial segregation between natives and immigrants. This is reflected in Leicester's dissimilarity index is 0.41 – one of the highest in Europe. In Bonn, by contrast, the proportion of immigrants varies less across grid cells, and grid cells with high proportions of immigrants are distributed across the entire FUA, including its suburban areas. Correspondingly, the spatial dissimilarity index for Bonn is 0.17, and thus significantly lower than in Leicester. See supplementary Figure A1 for additional examples.

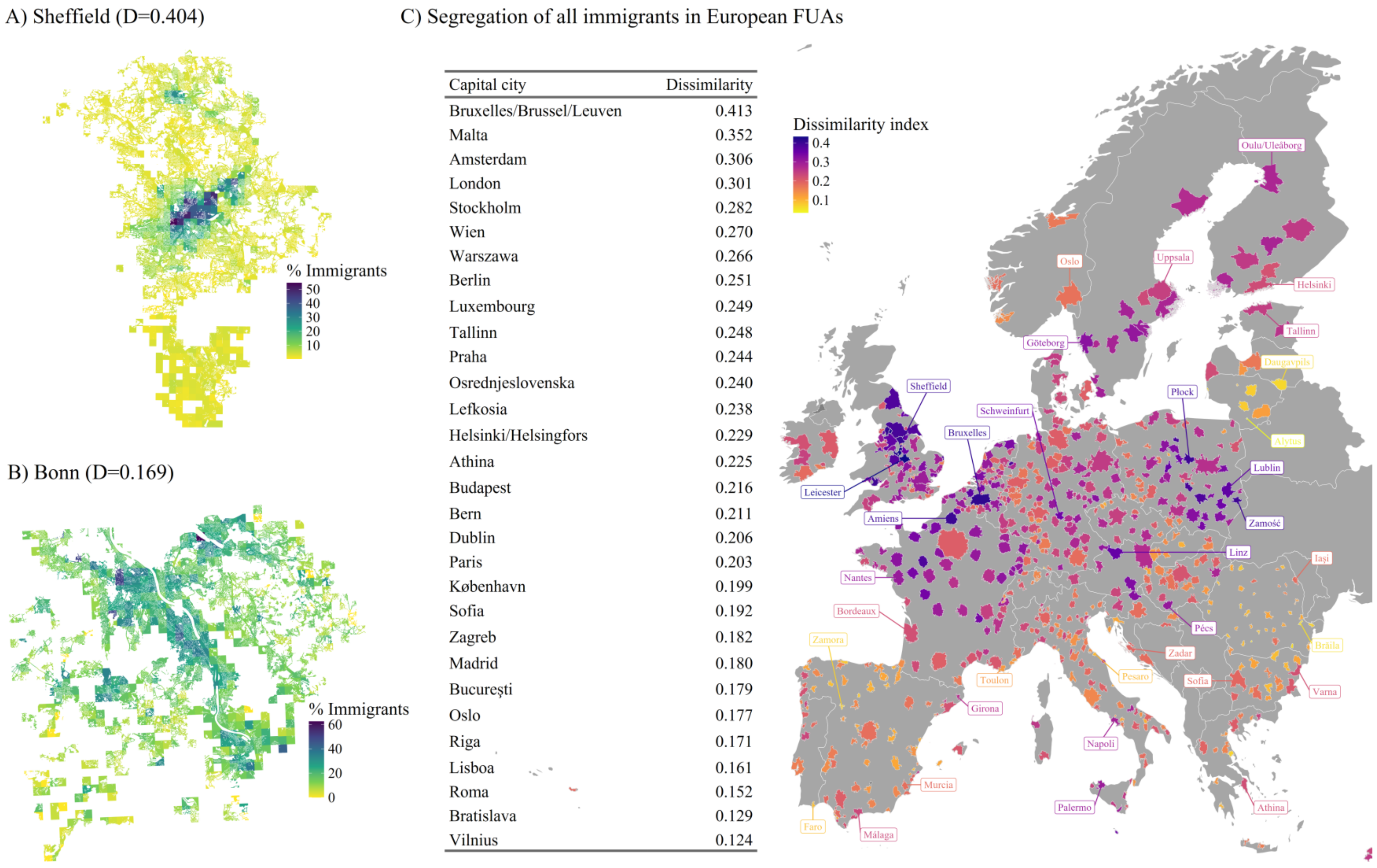
Mapping Segregation Levels Across Europe. Panel C of Figure 1 shows the segregation indices for all European capital cities. The Brussels-Leuven urban area (Belgium) is the most segregated capital urban area across Europe with a segregation index of 0.41, followed by Valetta (Malta), Amsterdam (Netherlands), and London (UK). The high segregation levels in Brussels, Amsterdam, and London are heavily driven by large-scale segregation patterns across city regions and suburban communities, as can be seen by high segregation indices on the 5km scale (see Appendix XX). A similar pattern has been documented for US metropolitan areas, particularlty for Back-White segregation patterns (Elbers 2024; Lichter et al. 2015; Reardon et al. 2008). The least segregated capital city at the 1km scale is Vilnius (Lithuania) with a segregation index of 0.12, closely follwed by Bratislava (Slovakia), Rome (Italy), and Lisbon (Portugal).

Panel D maps the spatial dissimilarity index D across all 711 FUAs, revealing that segregation is stronger in Western and Northern vis-à-vis Eastern and Southern Europe (see also Figure 2 A). Note that this ranking persists across a variety of segregation measures, spatial scales, and immigrant-minority groups (see supplementary Figure B1) – with the notatable exeption that EU-immigrants are, on average, more segregated in Eastern Europe than in Northern Europe (Figure B1, panel F). The FUAs with the highest levels of residential segregation are primarily located in the United Kingdom, northern France, and Belgium. Segregation levels are also substantial in the Netherlands, Germany (particularly East Germany), Denmark, Poland, Sweden, and Finland. FUAs in most Eastern and Southern European countries are considerably less segregated. There are, however, two notable exceptions to this pattern: Norwegian FUAs are considerably less segregated than those in other Northern European countries and Polish FUAs are more segregated than those in other Eastern European countries.

Comparing Patterns of Segregation across Europe. Figure 2 C) summarizes the distribution of these segregation indices in a boxplot for each country, with dots representing individual FUAs. Countries are ordered by their median segregation level, mirroring the Western/Northern vs Eastern/Southern gradient in segregation (see also Figure 1C and 2A). 41 % of the total variation in FUAs' segregation levels occurs between and 59 % within countries, suggesting that both country- and FUA-level correlates may be important. Especially in the the five most populous countries (Germany, France, United Kingdom, Itally, Spain), the gap between the most and the least segregated FUA exceed X.X standard deviations. The variation is strongest in England, where the dissimilarity index ranges from 0.09 in Stevenage to 0.43 in Leicester. Segregation ranges from 0.13 (Cannes-Antibes) to 0.40 (Amiens) in France, and from 0.10 (Konstanz) to 0.35 (Schweinfurt) in Germany. Variation is lower in Spain and Italy, where we measure segregation values from 0.07 (Zamora) to 0.27 (Las Palmas) and 0.10 (Pesaro) to 0.30 (Palermo), respectively.

We emphasise that the presented ranking pertains to segregation understood as the degree of spatial unevenness of immigrants' and non-immigrants' places of residence at a 1km scale. However – as emphasies by previous research (Lichter et al. 2015; Massey and Denton 1988; Reardon et al. 2008; Reardon and O'Sullivan 2004; Rüttenauer 2022; Spierenburg et al. 2023) – residential segregation is a multifaceted construct with many different dimensions, such as spatial isolation measured by the spatial isolation index P. Figure 2B shows that P is smaller than D for most FUAs, as indicated by dots located above the 45 degree line. In particular, many Polish/Eastern European FUAs score high on spatial dissimilarity but low on isolation (e.g. Zamość, or Płock). The reason for this is the relatively low number of immigrants living in these cities, and the heavy dependency of the isolation index on the share of immigrants within a city. Moreover, non-EU immigrants live more segregated than EU-immigrants across most cities (see Figure A2 A) with the expeptation of cities close to the EU border (such as Chelm, or Zamość). FUAs closer to the EU borders (like Larisa, Trikala, or Siedlce) are also more affected by outlier observations (see Figure A2 B). This could indicate some – despite generally very small – impact due to facilities for asylum seekers.

As we would expect (Lichter et al. 2015; Reardon et al. 2008), segregation indices decrease at larger spatial scales (see Figure A3 A), with Easter European cities becoming particularly less segregated when inclusing a 2km radius. Central and Norther European urban areas, in contrast, are also scoring relatively high on large-scale segregation (see Figure B1). Moreover, high segregation levels in Central European FUAs are to a substantial degree driven by difference between the urban core and surrounding suburban or rural areas. When we compare the dissimilarity index across the FUAs to dissimilarity indices in the core cities only (see Figure A3 B), we find that most cities are less segregate in the urban core as compared to the entire communiting zone of the FUAs. Outstanding examples are, for instance, Brussels (city-level: 0.15 vs FUA-level: 0.41), Amsterdam (city-level: 0.12 vs FUA-level: 0.31), or Strasbourg (city-level: 0.14 vs FUA-level: 0.32). This pattern is surprisingly similar to findings from the US context (Elbers 2024; Lichter et al. 2015; Logan et al. 2023).


A) Sheffield (D=0.404)

% Immigrants
50
40
30
20
10

B) Bonn (D=0.169)

% Immigrants
60
40
20
0

C) Segregation of all immigrants in European FUAs

Capital city	Dissimilarity
Bruxelles/Brussel/Leuven	0.413
Malta	0.352
Amsterdam	0.306
London	0.301
Stockholm	0.282
Wien	0.270
Warszawa	0.266
Berlin	0.251
Luxembourg	0.249
Tallinn	0.248
Praha	0.244
Osrednjeslovenska	0.240
Lefkosia	0.238
Helsinki/Helsingfors	0.229
Athina	0.225
Budapest	0.216
Bern	0.211
Dublin	0.206
Paris	0.203
København	0.199
Sofia	0.192
Zagreb	0.182
Madrid	0.180
București	0.179
Oslo	0.177
Riga	0.171
Lisboa	0.161
Roma	0.152
Bratislava	0.129
Vilnius	0.124

Dissimilarity index
0.4
0.3
0.2
0.1
Oulu/Uleåborg
Oslo
Uppsala
Helsinki
Tallinn
Göteborg
Daugavpils
Sheffield
Schweinfurt
Płock
Bruxelles
Alytus
Lublin
Leicester
Amiens
Zamość
Linz
Nantes
Iași
Bordeaux
Pécs
Zamora
Zadar
Brăila
Toulon
Pesaro
Sofia
Varna
Girona
Napoli
Murcia
Palermo
Athina
Faro
Málaga

Figure 1: Spatial distributions of the immigrant population in A) Sheffield and B) Bonn. C) Residential segregation between natives and all immigrants in 701 European FUAs with the spatial dissimilarity index of each capital city displayed in the table.

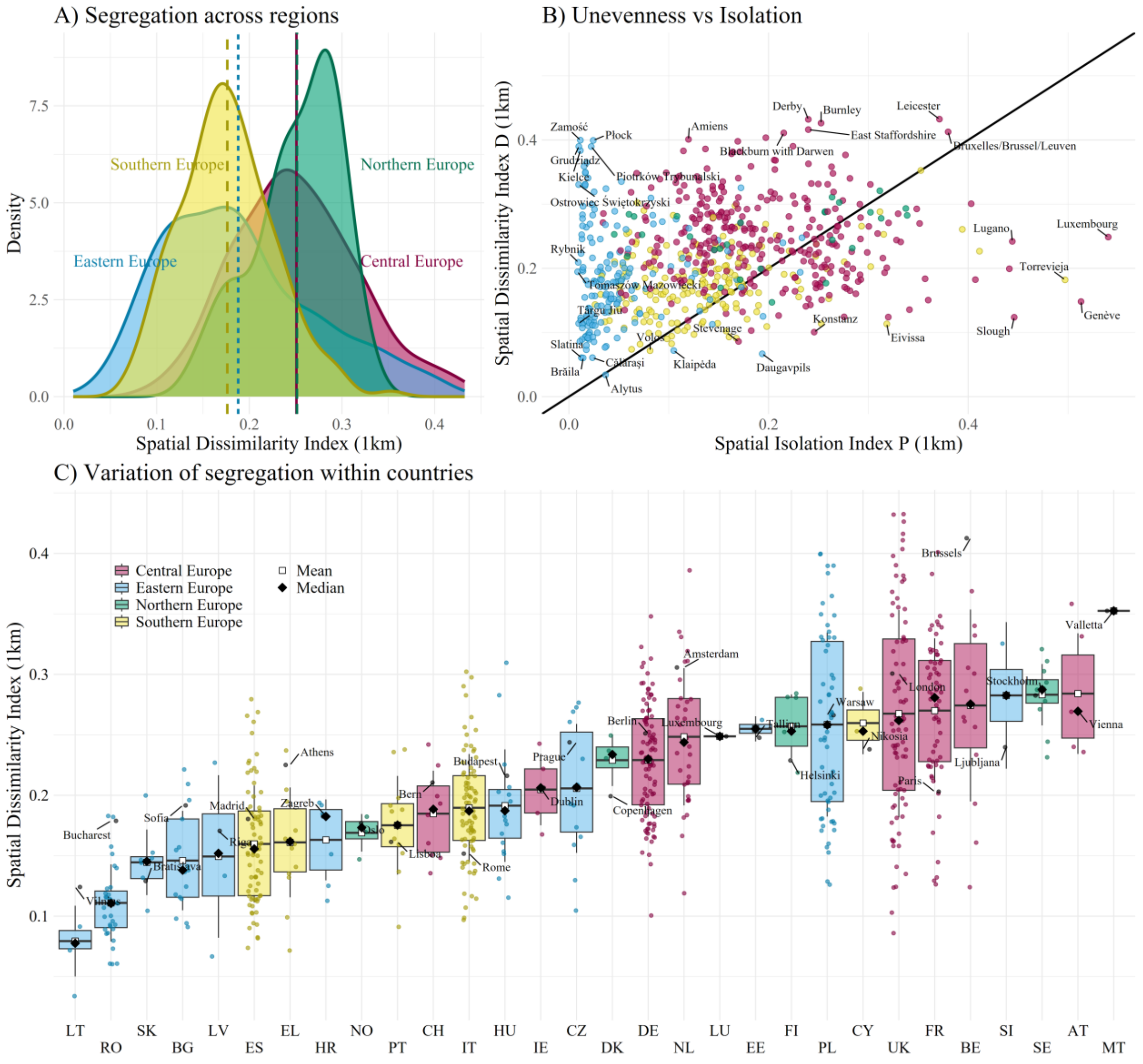


Figure 2: Segregation across Europe measured by the spatial Dissimilarity Index. A) Density distribution of segregation across regions; B) Comparison with spatial Isolation index; C) Residential Segregation in 701 FUAs across 30 countries and the FUAs including their capital cities. Note: The box of each boxplot represents the interquartile range (IQR) across FUAs and the whiskers extend to the smallest and largest values within 1.5xIQR. Countries are ordered by the mean of the segregation index across their FUAs. 701 FUAs. An interactive version of this Figure including the names of all FUAs can be found in the dashboard [link].

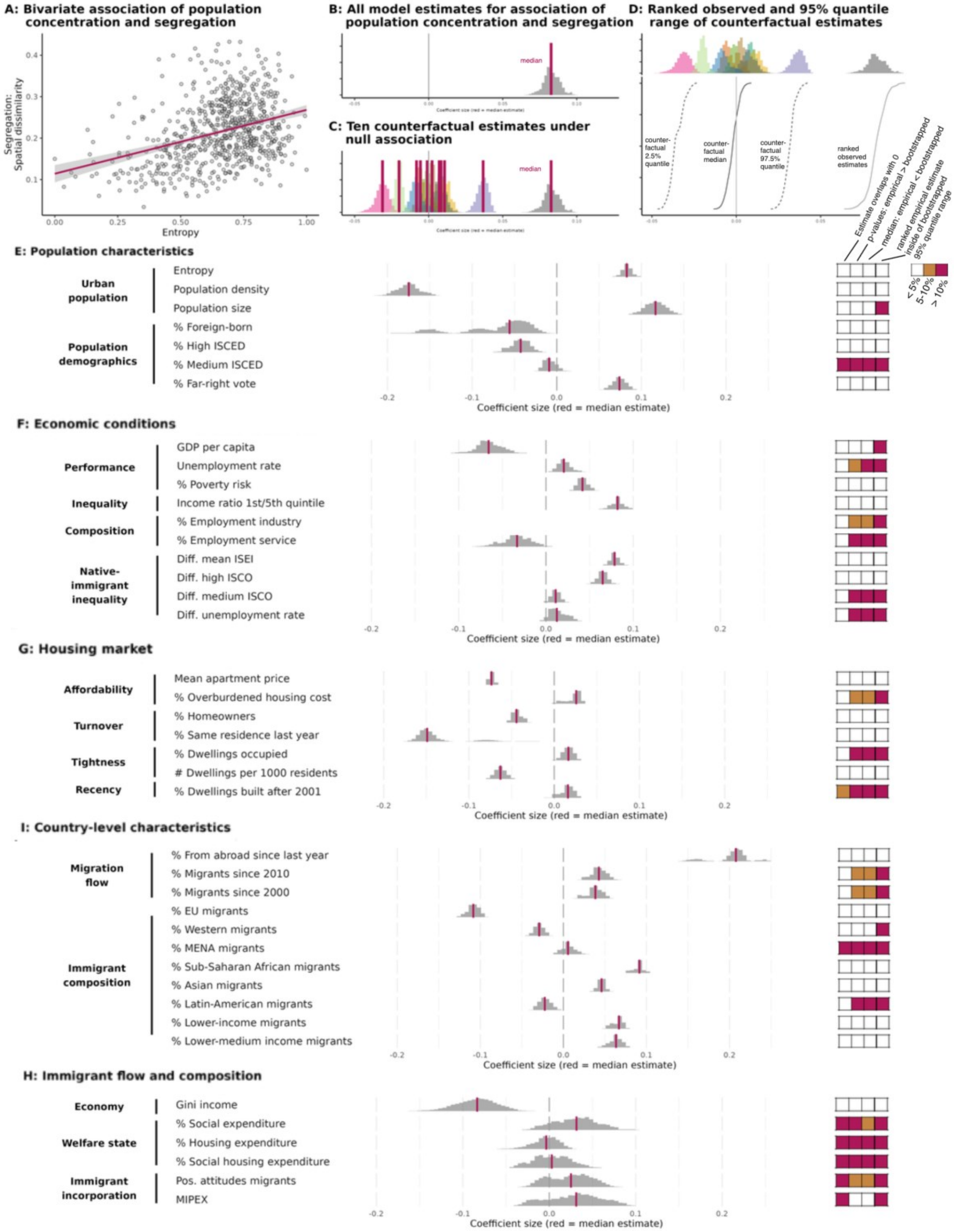


Figure 3: SCA of associations between levels of segregation and FUA and country characteristics Note: The universe of 'reasonable' model specifications excludes specifications including multiple variables from within the same variable subgroup (e.g., economic performance). For example, we do not estimate a model including GDP per capita and unemployment rate simultaneously.

We next investigate the association between segregation and FUA characteristics. Because we consider a wide range of potentially interrelated characteristics, we do not estimate a single "most likely" omnibus model for these associations. Instead, we borrow from the logic of specification curve analysis (SCA), estimating all *plausible and feasible* model specifications and assessing the robustness of associations across these specifications (Simonsohn et al. 2024). In total, we estimate all 8,012 model specifications that include six basic FUA population controls (population size, density, concentration, immigrant proportion, educational composition, and share of right-wing votes), up to four additional FUA-level correlates, and country fixed effects, yielding a distribution of coefficients for each predictor. Three increasingly conservative tests assess the robustness of each association across specifications (see Methods section for more information).

Figure 3 illustrates this logic using the example of the association between segregation and population dispersion (measured by population entropy), which captures whether the FUA is spatially concentrated or more even dispersed across the FUA. The bivariate association in panel A suggests that stronger population dispersion is linked to higher levels of segregation. Panel B displays the distribution of estimated associations across all specifications from the SCA. Test 1, the least conservative of our tests, evaluates whether at least 95% of all specifications predict the same sign for a covariate's association with segregation; in this example, the sign is identical across all specifications. Tests 2-3 further compare the *observed* distribution of estimates with *counterfactual* bootstrapped distributions that enforce a null association (Simonsohn et al., 2020). Next to the observed coefficients in grey, panel C illustrates ten example counterfactual distributions (statistical tests are conducted on a total on 500 bootstrapped distributions). Test 2 assesses whether the median observed estimate is larger than the median in at least 95% of the 500 bootstraps. Test 3 considers each model specification separately rather than the aggregate distribution and ranks observed estimates by size across specifications. For each specification, we then test if the observed estimate falls outside of the 95% quantile band of ranked counterfactual bootstrapped estimates. An association passes this test if observed estimates fall outside of the quantile band for at least 95% of all specifications. In what follows, given that test 3 is very conservative, we require an association only to pass tests 1 and 2 to label it as robust.

The association between population dispersion and segregation passes all three tests. This provides strong support for the idea that segregation of immigrants is stronger in FUAs whose population is dispersed more evenly across the entire urban area. When everyone lives very concentrated in only a few parts of the city, immigrant segregation is lower.

Figure 4 extends this example to the complete set of covariates, grouped into five thematic domains: population characteristics (A), economic conditions (B), the housing market (C), immigrant flow and composition (D), and country-level characteristics (E).

Panel A: Population characteristics. Next to the higher population concentration discussed in the example above, lower population density is also robustly associated with higher levels of segregation across all statistical tests. Furthermore, FUAs with larger populations are more segregated in all specifications, though the robustness of this link does not extend to our most conservative statistical test. Concerning population demographics, a higher overall proportion of immigrants is consistently linked to lower segregation, with exact effect sizes varying widely across specifications. All tests further support that a larger proportion of highly educated residents and a smaller group of right-wing voters predict lower levels of segregation.

Panel B: Economic conditions. All indicators of economic performance—higher GDP per capita, lower poverty risk, and lower unemployment rate—are consistently associated with lower segregation levels. While robustness varies across indicators, this suggests that favourable economic conditions predict lower levels of immigrant segregation. Segregation is also consistently higher in FUAs with higher economic inequality, but, by contrast, higher disparities *between immigrants and natives* in terms of occupational status are associated with lower levels of segregation. However, this pattern does not extend to differences in unemployment between natives and immigrants, which only affects a relatively small proportion of both groups. Finally, the size of the agricultural, industrial, and service sectors is not consistently related to segregation.

Panel C: Housing market. Several characteristics of local housing markets are related to segregation levels but associations strongly depend on the specific indicators considered. FUAs with high apartment prices consistently have lower levels of segregation, while a higher proportion of households with high housing expenses (> 40% of income) is not systematically linked to segregation. A higher proportion of homeowners and a higher proportion of stationary households (same residence for at least a year) are linked to lower segregation, in line with an inhibition of segregation processes by low housing turnover. Tighter housing markets—characterized by fewer dwellings per resident and a higher occupancy rate—are associated with higher segregation levels, although the first indicator proves more robust. By contrast, more recently built housing is unrelated to immigrant segregation.

Panel D: Flow and composition of immigrant population. Segregation is higher in FUAs with larger recent inflows of immigrants. However, associations are only robust when considering inflow from the previous year – which may indicate popular destination hubs for international migration. While point estimates also suggest higher segregation in FUAs with more substantial in-migration from the 2000s on, these links are not robust to the more conservative tests. We find no link between segregation and the proportion of immigrants from MENA, Latin American, or 'Western' countries. Otherwise, however, immigrant composition is related to segregation, with segregation consistently higher in FUAs with a lower proportion of EU immigrants, a higher proportion of immigrants from Sub-Saharan Africa and Asia, and a higher proportion from lower- and lower-middle-income countries.

Panel E: Country characteristics. To study the link between country characteristics and segregation, we remove country fixed effects and switch to a random-intercept multilevel SCA.

As in the previous analyses, we retain all FUA controls and all potential combinations of up to four additional FUA characteristics, and add up to three country-level characteristics, for a total of 15,820 models. We find that, other than at the FUA level, country-level economic inequality is robustly linked to lower levels of segregation. By contrast, country-level spending on housing and social issues, as well as attitudes towards immigrants and migration policy, are not consistently linked to segregation. In each case, some specifications support a positive, and some a negative association with segregation.

Discussion

Main finding: in 2 sentences:

The present study provides a comprehensive overview of immigrant-native residential segregation across all urban areas in 30 European countries, revealing considerable variation in the level of segregation both across and within countries. 60% of the total variation in segregation is between countries, while 40% is between urban areas within the same country. Segregation is stronger in Western and Northern Europe than in Eastern and Southern Europe. Urban areas with weaker economic performance, a tight and high-turnover housing market, a larger proportion of non-EU immigrants, and weaker immigrant-native inequalities have systematically higher levels of segregation.

Implications (in a way these are the contributions):

Our study makes two key contributions. First, the results expand, update, and systematize our knowledge of immigrant-native segregation across Europe. Moving beyond existing studies (e.g., Marcincack et al 2023, Benassi 2020), our study uses recent census data and a harmonized definition of urban areas to document segregation for all urban areas in 30 European countries, considering both evenness and cross-group exposure of the immigrant-native population distribution, as well as neighborhood resolutions ranging from 500m to 5km. While such large-scale comparisons of segregation levels across urban areas have been common in the U.S. (e.g., Carlson et al 2025, SF; Lichter et al. 2024, Demography; …), equivalent evidence in Europe has been missing due to data limitations. Previous comparative studies were restricted to data until 2011 and urban areas in a maximum of eight European countries, preventing a comprehensive assessment of variation across Europe.

Second, our comprehensive analysis of a wide range of FUA and country characteristics shows which macro-level traits are systematically associated with segregation and which are not. Some of our findings closely align with long-standing theories about the emergence of segregation. For example, we find that local housing markets with higher turnover rates are related to higher segregation. This resonates with Schelling's classic preference-based segregation model, in which segregation emerges as the number of homophilous residential moves increases (Schelling 1969). Theories of place stratification commonly emphasize the role of discrimination for segregation, suggesting that segregation should increase with the support for far-right parties and the presence of stigmatized origin groups – patterns we also find in our analysis. Other findings conflict with existing theory. For example, the finding that segregation is stronger in places with higher levels of immigrant-native socio-economic inequalities contradicts spatial assimilation theory (Fossett 2011; Iceland and Wilkes 2006), which links structural assimilation to residential integration. This invites further theoretical and empirical research on whether upwardly mobile immigrants indeed move out of ethnic enclaves and which other mechanisms prevent residential integration as natives and immigrants become more similar economically. Similarly, while we generally find higher segregation levels at greater proportions of stigmatized minority groups, we do not observe a systematic link for immigrants from the Middle East and Northern Africa, even though much of European public discourse surrounds these origin groups. Finally, general spatial population characteristics, such as population size, density, and dispersion, consistently appear among the strongest predictors of segregation in our analysis. As existing theory is largely silent on the social mechanisms that link these characteristics to segregation, we encourage further theorizing on the role of these spatial population factors.

Limitations:

We acknowledge three main limitations of the present study. First, the harmonized census data distinguishes only between immigrants and natives. Accordingly, we can neither differentiate by origin country, length of residence, and socio-economic status, nor make any statements about the residential situation of descendants of immigrants. However, these are of core interest for tracking long-term integration patterns.

Second, the grid-cell resolution of 1km does not allow for analysing micro-segregation. We therefore cannot assess any patterns of segregation within each 1km grid cell. As a result, we necessarily miss local sorting across residential blocks, particularly taking place in densely populated urban areas.

Third, the analysis of correlates of segregation at the urban area- and country level does not allow to identify causal effects. Local patterns of segregation emerge over decades as a result of individuals' moving behavior in response to a range of social conditions. (xxx) Even the large number of covariates included in our analyses necessarily miss important information on the conditions under which segregation emerged (e.g., geographic barriers in cities, details of city-specific housing policies, the distribution of social housing dwellings …) and how they interacted with one another (e.g., (Tóth et al. 2021)). At the same time, segregation itself can shape other local outcomes, such as the openness to immigration and migrants' economic success.

Opportunities for future research:

Despite these limitations, our documentation of segregation across 717 urban areas in 30 European countries and exploratory analysis of their macro-level correlates offer several opportunities for future research. The substantial variation in segregation across and within countries we identify raises questions of whether regional differences in segregation are also mirrored in differences in immigrants' experiences and integration outcomes across contexts. In addition, our systematic documentation of segregation indices can help researchers strategically select specific urban areas for small-N in-depth case studies to assess the interplay of different local characteristics in shaping segregation (cf. Bruch and Swait 2019, Demography; XXX). At the same time, the identification of a range of local characteristics that are—or are not—robustly associated with segregation invites both further theory building and empirical research. In terms of theory, both findings that conflict with existing theoretical frameworks and factors that have not received much theoretical attention, but were highly predictive in our analyses, call for further refinement of theories on the macro-level determinants of segregation. In terms of empirical research, we particularly encourage further research that tests whether the associations we have documented as robust indeed reflect causal effects of urban area and country characteristics on segregation. Here, our comprehensive exploratory analysis can help select both contexts and local characteristics that lend themselves to a more credible analysis of causal effects.

Methods

Data

Functional Urban Areas. To identify urban areas across Europe, we rely on the joint Eurostat/OECD classification of Functional Urban Areas (FUAs). Each FUA consists of an urban center/city and its commuting zone, i.e., all surrounding areas in which at least 15% of the population commute to the urban center (for details, see Eurostat 2025b). This uniform way of identifying urban areas across all 30 countries avoids measurement issues arising from country-specific variations in administrative definitions of urban areas [and has become standard in the comparative European literature on segregation (Marcinzak et al, Benassi et al. 2020)]. . We use shapefile information on the geographical boundaries of FUAs provided by Eurostat (Eurostat XXXX).

Local native and immigrant population. To identify the spatial distribution of the local native and immigrant population, we rely on data from the 2021/2022 census conducted in all 30 countries. Based on the census data for the 27 EU member states, Switzerland and Norway, Eurostat provides aggregated and harmonized information on the population composition in all 1x1 km grid cells (Eurostat 2025a). These data provide information about the number of individuals residing in each grid cell and whether they were born in the country of residence, in another EU country, or in another non-EU country. We obtain comparable data for the United Kingdom from three separate sources: The 2021 census for England and Wales, the 2022 census for Scotland, and the 2021 census for Northern Ireland. While the latter is available in a 1x1 km grid cells format directly comparable to the remaining European data, the other two sources provide the relevant information at the spatial resolution of Lower Statistical Output Areas (LSOAs). Within FUAs, XX% of LSOAs cover an area smaller than 0.XX square km. We aggregate the LSOA information to 1x1 km grid cells (see Part X of the Appendix for more detail).

FUA and country-level correlates of segregation. To examine the correlates of residential segregation, we collect FUA- and country-level information from Eurostat, the OECD, the UN, the European Election Database, the European Social Survey, and the Migrant Integration Policy Database. Missing values were imputed using multivariate imputation by chained equations (van Buuren and Groothuis-Oudshoorn 2011). For each variable, Table AX in the Appendix lists the definition, the spatial level of measurement, the year of measurement, the providing institution, the access link, and the proportion of imputed values. We merge the FUA-level segregation indices with the FUA- and country-level variables.

Measures

Following the comparative literature on residential segregation, our primary measure of segregation captures the *unevenness* of the distribution of immigrants and natives across the urban area, i.e., the degree to which both groups live spatially separated from one another (Reardon 2004). Segregation is lowest when each spatial unit contains the same proportion of immigrants as the overall urban area, and highest when all immigrants live is entirely homogeneous neighborhoods (Massey & Denton, 1988). We measure unevenness at the FUA level with the spatial dissimilarity index $\widetilde{D}$. Compared to the non-spatial version of the dissimilarity index D, the spatial index $\widetilde{D}$ takes the geographic locality of the grid cells into account by interpolating population characteristics within a given radius. It is defined as:

$$\widetilde{D} = \sum_{m=1}^{M} \int_{p\in R} \frac{\tau_p}{2TI} \left|\tilde{\pi}_{pm} - \pi_m\right| dp,$$

Where, $\tilde{\pi}_{pm}$ refers to the proportion of group m in the local neighbourhood around each 1x1 km grid cell p, π_m to the overall proportion of group m in the FUA, τ_p to the population density (number of residents) in grid cell p, T to the total population of the FUA, and I to a normalization constant ensuring that $\widetilde{D}$ falls within the range of 0 and 1, calculated as $I = \sum_{m=1}^{M}(\pi_m)(1-\pi_m)$ (Reardon and O'Sullivan 2004). Our application has two groups m_0 and m_1: immigrants and natives. Intuitively, $\widetilde{D}$ aggregates the deviation of the local immigrant-native composition of all 1x1km grid cells in a FUA from the FUA's mean immigrant-native composition weighted it by local population density. Higher values therefore imply that the local immigrant-native compositions deviate more strongly from the mean composition of the FUA, i.e., that immigrants and natives live more segregated from each another.

We prefer the spatial dissimilarity index $\widetilde{D}$ over other measures of unevenness. Compared to the spatial Theil index $\widetilde{H}$, a desirable feature of $\widetilde{D}$ is that its two-group measure is scale invariant to the overall population of the city (Reardon and O'Sullivan 2004). Compared to the traditional dissimilarity index D, a central advantage of $\widetilde{D}$ is that it accounts for potential geographic clustering of localities with similar immigrant-native composition. The traditional dissimilarity index is unaffected by whether grid cells with high immigrant concentration are located in close proximity to one another, rather than randomly spread across the FUA. By contrast, the spatial dissimilarity index accounts for such clustering by explicitly considering the geographic arrangement of grid cells (Lee, 2008; Reardon and O'Sullivan, 2004, Reardon 2008; Ruttenauer, 2022), with index values higher at stronger clustering. For a broader overview of available measures, see Tivadar (2019).

While our main analysis focuses on unevenness measured by the spatial dissimilarity index, we also provide additional analyses on isolation as a second key dimension of segregation (see Figure 2B and Supplementary Material X) (Reardon 2008). The spatial isolation index $\tilde{P}^*$ captures to what extent immigrants are exposed to immigrants rather than natives in their local environments. It is defined as:

$${}_m\tilde{P}^*_m = \int_{q\in R} \frac{\tau_{qm}}{T_m}\tilde{\pi}_{qm}dq.$$

with

$$\tilde{\pi}_{pm} = \frac{\tilde{\tau}_{pm}}{\tilde{\tau}_p}.$$

(replace q with p in first formula!?)

where τ_{pm} denotes the population density of group m for the local grid cell p, and T_m is the total population of group m. $\tilde{\pi}_{pm}$ corresponds to the proportion of group m in the local neighbourhood around grid cell p. Intuitively, the isolation index quantifies the average proportion of immigrants in immigrants' local environment. It is thus by definition highly depended on the share of immigrants living in a city (Reardon and O'Sullivan 2004). All spatial segregation indices are calculated using the R package seg (Hong, 2014).

Statistical Methods

To investigate which FUA- and country characteristics are robustly associated with residential segregation, we use specification curve analysis for inference with non-experimental data as described in Simonsohn et al. 2024.

We first define the universe of feasible and plausible specifications. In the analyses with country fixed effects, this includes all models with basic population controls and up to four additional FUA characteristics. We allow arbitrary combinations of FUA characteristics that do not aim to capture the same underlying construct defined at the subgroup level of variables (e.g., because both GDP per capita and the unemployment rate capture economic performance, they are not included in the same model; however, GDP per capita and the ratio of the 5th and the 1st income quintile can be in the same model because the former measures economic performance, while the latter measures economic inequality). Table X in Supplementary Material Y provides an overview of all variable subgroups and the combinations of variables that are (not) estimated in the same model. These criteria result in a total of 8,012 fixed-effects models.

In the analysis including country-level characteristics, we use random-effects multilevel models with random intercepts and, next to four FUA characteristics, up to three country characteristics. This results in a total of 15,XXX random-effects multilevel models.

For each variable v, the specification analysis produces a distribution of Kv point estimates. In Test 1, our least conservative test, we assess whether the vast majority—at least 95%—of these estimates fall to one side of the null side, indicating a robust association. For Tests 2-3, we compare the observed specification curve to counterfactual specification curves obtained by bootstrapping. For each variable v, we estimate a counterfactual outcome yKy for all K specifications that imposes a null effect of the variable v on segregation (by defining yKy as the original outcome y minus the estimated effect bv of variable v multiplied with the observed v); all other FUA and country characteristics remain unchanged. From this dataset, we then draw samples of the size of the original number of FUAs (711) with replacement and estimate all specifications Kv on those data. Repeating this process 500 times provides us with a bootstrapped distribution of counterfactual estimates under an imposed null effect of each variable v. Test 2 compares the median estimate from the observed specification curve to the median estimates of the counterfactual specification curve; if the observed median is more extreme than the counterfactual medians in at least 95% of the bootstrapped distributions, the variable passes Test 2. Test 3 ranks the estimates in both the observed specification and the counterfactual specification curves by size. For each specification, it then tests whether the observed estimates fall outside of the 95% quantile range of the corresponding counterfactual estimates. The variable passes Test 3 if the observed estimate falls outside of the 95% quantile range for at least 95% of all specifications. In Supplementary Material X, we introduce a range of alternative tests, the results of which we show to be highly consistent with Tests 1-3 discussed above.

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