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Measuring residential segregation in multi-ethnic and unequal European cities

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Abstract

Immigration flows and social inequalities reflect increased social and multi-ethnic segregation in contemporary urban Europe. For a better understanding of these processes, the present study investigates the main strengths of the multi-group residential indices, testing sensitivity and reliability under different metropolitan contexts in five European countries. These indices focus on different research dimensions and approach multi-group residential segregation conceptually and mathematically in a different way. A multivariate exploratory data analysis was adopted to classify the observed segregation patterns into a few homogeneous types and to delineate the multivariate relationship between the indices. The results of principal component analysis demonstrate that the indices assessing uniformity and disproportionality of the social groups analysed (H and D) contribute largely to the diversification in today's multi-ethnic communities, clarifying the importance of the dimension of evenness. Our results highlight how segregation is more evident in economically disadvantaged metropolitan regions with high levels of social vulnerability.

INTRODUCTION

The social integration of the growing immigrant flows and promotion of more cohesive and inclusive societies are major challenges facing Europe today (Smith, 2019). Earlier studies have analysed how recent inequalities in wealth and income within advanced societies (Malmberg & Clark, 2021; Yao et al., 2019), increasing ethnic diversity (Catney, 2016; Logan & Zhang, 2010; Zwiers et al., 2018), and unbalanced international and interregional migration flows (Ciommi et al., 2018; Cuadrado-Ciuraneta et al., 2017; Di Feliciantonio et al., 2018), all play key roles in metropolitan transformations (Czaika & De Haas, 2014; Panori et al., 2019; Portes, 2000). These challenges have brought the relationship between integration, social and ethnic segregation, and their intrinsic measurement, to the forefront of the political and social agendas in European countries (Coulter & Clark, 2019; Piekut et al., 2019). Earlier studies on the social repercussions of living in segregated social settings (e.g. Badanta et al., 2021; Casey, 2016) delineate the importance of class and ethnic segregation. They also point out the intrinsic association of social segregation with economic advantages (Kaplan, 1998; Peach, 1996; Portes & Manning, 1986; van Kempen & Ozuekren, 1998). More recent works have documented the negative impact of residential segregation, arguing how the residential segregation of minority groups leads to a set of negative effects (i.e. Charles, 2003; Sampson et al., 2008). In particular, a high level of residential segregation reinforces the social exclusion of certain groups, and is detrimental to social cohesion (Amin, 2002; Peterson, 2017; Putnam, 2007; Sturgis at al., 2014; van Ham & Manley, 2010).

Additional studies argue that geographical dispersion, and thus less segregation, does not ensure a broader (cultural or social) integration, nor a greater sense of belonging to the host society (Wright & Ellis, 2000). Assuming that segregation reflects social inequalities (Yao et al., 2019), the notions of segregation and integration largely depend on the particular social group under investigation (Krysan et al., 2017). A refined analysis of social changes in specific economic contexts will contribute towards delineating the relationship between ethnic segregation and the design of inclusive policies (Allen et al., 2004; Hochstenbach & Musterd, 2018; Iglesias-Pascual et al., 2019; Johnston et al., 2014). In this regard, expanding immigration flows and rising economic inequalities have produced a generalized increase in social segregation in European cities (Lymperopoulou & Finney, 2017; Monkkonen et al., 2018; Tammaru et al., 2016, 2017). Earlier studies have pointed out the limitations of classical residential segregation approaches since they do not usually consider the background context (Bolt et al., 2010). However, measurement tools that allow for a more accurate analysis of the multi-ethnic dimension of society (Kramer & Kramer, 2019; Reardon & Firebaugh, 2002; Yao et al., 2019) and its relationship with the demographic and socio-economic dimensions (Benassi, Iglesias-Pascual, et al., 2020; Finney et al., 2015) will help to provide us with the necessary knowledge about the current ethnic segregation in European societies.

The present study contributes to such challenging issues with a refined analysis of statistical data derived from *D4I - Integration of migrants in cities* (Tintori et al., 2018), a data challenge initiative promoted by the European Commission. More specifically, our work investigates (and compares the fit of) multi-group segregation indices at the level of metropolitan Functional Urban Areas (hereafter 'FUA') on regular lattice data (grid) for selected European countries (Germany, Ireland, Spain, the Netherlands and United Kingdom). These are a subset of the countries involved in the D4I data challenge that define their migrant populations with the same criterion (i.e. country of birth). We believe that by selecting these countries, we can analyse the main models of welfare regimes and housing systems that have been prominent in the academic debate on the residential segregation of immigrants in Europe (Arbaci, 2019).

Two-group indices assess phenomena occurring when a given group (usually the minority group) is not distributed spatially in a similar way with respect to another (usually the majority group). In contrast, multi-group indices approach residential segregation as a phenomenon which concerns all the population groups which reside in a given area simultaneously (Reardon & Firebaugh, 2002). According to the most recent literature, two-group indices are ineffective in representing contemporary societies with multiple population groups (identified through ethnicity, race, religion and citizenship) which coexist within the same context (Benassi, Iglesias-Pascual, et al., 2020).

Based on these premises, our study has three main aims. The first is to identify apparent and latent information from a comprehensive set of multi-group residential indices using a multivariate analysis to classify segregation patterns. Secondly, we aim to delineate the relationship between the above indices, each of which pertains to different dimensions and which were derived by approaching multi-group residential segregation conceptually and mathematically in a different way (Reardon & Firebaugh, 2002). Finally, we test the sensitivity and responsiveness of multi-group segregation indices by comparing metropolitan contexts defined with the same functional logic ("FUA"), using the same base geography (grid) and input data (2011 census). By following these steps, our study can infer the existence of common patterns of residential segregation among FUAs from the latent relationship between multi-group indices and background variables.

The present paper is organized as follows: in the next section, we offer some reflections on how residential segregation is measured. Next, we describe data and methods, focusing on the characteristics and properties of the multi-group indices. In the penultimate section, we present our results, and this is followed by a discussion and our conclusions in the final section.

MEASURING RESIDENTIAL SEGREGATION

Tools used to assess residential segregation should be adapted to the objectives, scales, and units of analysis on which social science is built (de Bézenac et al., 2021; Morrill, 1991). Earlier studies, such as the seminal contributions of Duncan and Duncan (1955) and, later, Massey and Denton (1988), conceptualize residential segregation as the degree of spatial separation between two or more population groups in a given context (Yao et al., 2019). In the past, the two study groups used to be blacks and whites (e.g. Farley, 1977), while in recent times, they consist of an immigrant (foreign) nationality and the host society (e.g. Kauppinen & Van Ham, 2019; Wessel et al., 2018). These indices are traditionally based on single-value results (i.e. global indices), and are descriptive in nature and intrinsically a-spatial, relying only on the numerical values in each observation unit without taking into account the situation in the surrounding areas or the spatial patterns in rates (Jones et al., 2015). Instead, they are easy-to-interpret indices that investigate dissimilarity, isolation and exposure – among other dimensions of residential segregation – and allow for a comparative analysis across metropolitan areas (Arcaya et al., 2018; Reardon et al., 2008). Nevertheless, these indices typically do not capture complex residential patterns across racial and social groups (de Bézenac et al., 2021; Clark et al., 2015).

The increasing ethnic diversity of Western societies (Long & Zhang, 2010; Zwiers et al., 2018) has generated an important academic debate regarding the importance of the idea of "super-diversity" and its social and analytical implications (Meissner & Vertovec, 2015; Vertovec, 2007). In this context, it should be noted that the size of the (resident) foreign population in a given city, the associated economic conditions and the migratory trajectory of the surrounding region all play a key role in the degree of ethnic and cultural diversity and the residential segregation patterns (Marcińczak et al., 2021; Pisarevskaya et al., 2021). This undeniable social reality suggests that a dichotomous analysis of segregation (i.e. the ones typically based upon traditional two-group segregation indices) cannot properly explain the current segregation patterns of a multi-racial society (Kramer & Kramer, 2019; Reardon & Firebaugh, 2002). From the multi-racial perspective, the concept of residential segregation can be interpreted as the extent to which individuals from different groups occupy and experience different social environments (Reardon & O'Sullivan, 2004). Research using multi-group segregation indices is based either on traditional a-spatial indices (Reardon & Firebaugh, 2002; Reardon & O'Sullivan, 2004), such as Theil's entropy index (H) or the dissimilarity index (D), or on spatially explicit indices (Wong, 1997, 2005).

Another key factor is the role of the geographical scale of analysis and its effect on segregation indices (Clark & Östh, 2018; Jones et al., 2015; Marcińczak et al., 2021; Olteanu at al., 2019). No one scale can be considered more appropriate than others when studying segregation, especially when it comes to intra-urban studies (Duvernoy et al., 2018; Salvati et al., 2018; Zambon et al., 2018). In fact, the relationship between the degree of segregation and the spatial scale adopted often differs from one city to another (Lan et al., 2020). Even multi-scale studies have shown that residential segregation can vary according to the ethnic group analysed in the same city (Catney, 2018; Lee et al., 2008). This means that communities can be highly segregated at the macro-scale level and yet much less segregated at the micro-scale level (Simpson & Jivraj, 2015), because racial/ethnic and economic segregation at the metropolitan scale may be lower, and yet it may increase when analysed within smaller geographical areas, either at the district or census tracts level (Arcaya et al., 2018). This aspect has led recent studies to develop a multi-scale approach when analysing residential segregation and designing bespoke/egocentric neighbourhoods according to different measurements of radius or areas based on population size (e.g. de Bézenac et al., 2021; Manley et al., 2019; Marcińczak et al., 2021; Östh et al., 2015; Petrović, et al., 2018; Wright et al., 2011). However, in the studies that address the relationship between segregation and the spatial scale, there is little reflection that goes beyond the merely spatial dimension. Deciding which scale is the most suitable for analysing the social consequences of the different degrees of segregation is an important outcome of this reflection.

Finally, it should be highlighted that, if a comparative analysis is to be developed to detect the existence of common comparative patterns or different behaviours at the level of large and middle urban areas, it is advisable to use a broader scale that allows for comparison across different types of urban centres (Benassi, Iglesias-Pascual, et al., 2020; Rey et al., 2021). This is where the use of FUAs, as a commuting space and daily living space, makes the most sense (Dijkstra et al., 2019). In fact, these macro analyses between large regional models should prevent us from concentrating exclusively on the study of the most important (or populated) urban centres, and focus rather on the considerable number of cases that permit a refined investigation of the existence of common (or divergent) patterns of segregation at the regional level (Benassi, Iglesias-Pascual, et al., 2020; Marcińczak et al., 2021; Pisarevskaya et al., 2021).

DATA

The data used in this contribution were provided by the Data Challenge on "*Integration of Migrants in Cities*" (D4I). D4I is an initiative launched at the end of 2017 by the Joint Research Center (JRC) – Knowledge Centre on Migration and Demography (KMCD) of the European Commission to disseminate scholars and researchers with a data set of population estimates for grids which permit the analysis of concentrations of migrants in selected European Union cities with a high spatial resolution.[1]

This data set was based on ad hoc extractions of the 2011 Population and Housing Census data provided by the National Statistical Institute of 8 EU member states (France, Germany, Ireland, Italy, Portugal, Spain, The Netherlands and the United Kingdom). The results of the spatial processing of the original data are an estimation of population by place of birth or citizenship (depending on the country), for a uniform grid (cells of 100 by 100 meters) in the countries involved in the initiative (Tintori et al., 2018). This means that data are comparable from a geographical point of view. Grid data are very useful when it comes to measuring specific processes like residential segregation, where spatial pattern alterations produced by tract level analysis tend to be highly localized (Catney & Lloyd, 2020; Lee et al., 2008; Mazza, 2020). In the last few years, scholars worldwide have been involved in several initiatives to produce grid data on population attributes (Batista e Silva et al., 2013; Deichmann et al., 2001; Leyk et al., 2019; Lloyd, Catney, et al., 2017; Lloyd, Sorichetta, et al., 2017). Grid data are particularly suitable for between-country comparisons, and are also useful when compiling official statistics, especially when studying the causes and effects of socio-economic and environmental phenomena. Eurostat, for instance, stresses the importance of using grid data in these kinds of studies because same-sized grid cells (i) allow an easy comparison between any kind of quantitative population attribute which is stable over time; (ii) can be easily integrated with other scientific data; (iii) can be constructed hierarchically in terms of cell size to match the study area and, finally, (iv) can be assembled to create areas for specific purposes and study[2]. The production and availability of grid data on population depend on the type of data available from official statistics. As clearly explained by Catney and Lloyd (2020), in countries where geo-referenced household-specific data are normally available, grid population counts are easily produced by aggregating elementary data. In other cases, or for other population variables, where gridded data are not provided, estimation procedures can be used, although these can lead to minor or even major errors. The different follow-up methods range from the simplest (e.g. weighting approaches) to the most sophisticated, which are based on the use of ancillary data source, such as land use (Catney & Lloyd, 2020). For an overview of methods for producing grid data, see, among others, Leyk et al. (2019), Lloyd, Catney, et al. (2017), Lloyd, Sorichetta, et al. (2017), and Batista e Silva et al. (2013). In this paper, we used the grid data of population counts produced by the Joint Research Center, focusing on the input data of the 2011 Population Censuses produced by the National Statistical Institute of the countries involved in the D4I initiative through a complex estimation procedure. Details about the methods applied for processing the original data and for technicalities regarding estimation of the data used here can be found in the JRC Technical Report (Alessandrini et al., 2017). It is important to underline that we have chosen to work only with micro-level grid data, because this spatial scale allows us to measure not only the level of segregation but also other social variables, such as the degree of inter-ethnic contact at the local level or discrimination in the residential market (Catney & Lloyd, 2020; Imeraj et al., 2020; Vogiazides, 2018). In turn, this contact between the host society and the foreign population has been shown to be a key factor in constructing the social integration process (Layton & Latham, 2021; Peterson, 2017; Vertovec, 2021). We hope that, by the end of the 2021 census round, other grid data based on migrant populations will be released so that we can address the study of residential segregation across time and using comparable geographical areas.

However, it is important to underline that the D4I data are drawn from two different statistical concepts as far as the origin of migrants is concerned: the country of citizenship (Italy and France) and the country of birth (Germany, Ireland, Portugal, Spain, The Netherlands and the United Kingdom). Both approaches are based on information provided by the 2011 general population censuses (Benassi, Bonifazi, et al., 2020). However, the two criteria to identify the target population determine aggregates that are also significantly different from each other (Bonifazi & Strozza, 2006). For a better comparison between different urban contexts, we have selected a subset of countries: Spain, the Netherlands, the United Kingdom, Ireland and Germany. We chose these countries because all of them used the same criterion to identify their migrant populations (country of birth), which provides with an explicit distribution of single country of birth broken down by grid level.[3]

GEOGRAPHICAL AREAS

Our analysis takes as its analysis domain the major Functional Urban Areas (FUAs) of the five countries. The FUAs are functional partitions proposed by the OECD on the basis of a clearly defined methodology that refers to daily people's job-related movements. The FUAs provide a functional definition of cities and their area of influence (commuting zone), maximizing international comparability and overcoming the limitations and drawbacks of the administrative approaches, thereby ensuring a minimum link to the government levels of the city or metropolitan area at large (OECD, 2012).

The FUAs were classified according to their demographic size into 4 categories: small urban areas (50,000–100,000 inhabitants); medium-sized urban areas (100,000–250,000 inhabitants); metropolitan areas (250,000–1.5 million inhabitants) and large metropolitan areas with over 1.5 million inhabitants. Here, we focus our attention on the last two categories of FUAs: metropolitan and large metropolitan areas (Table 1). These are the territorial contexts in which the presence of foreigners is comparatively higher and where ethnic diversity is more intense (Benassi, Bonifazi, et al., 2020; Feitosa et al., 2007).

The population size of each selected FUA varies from a minimum of (at least) 500,000 inhabitants (e.g. in the case of Freiburg (529,806 residents), the smallest of the 53 FUAs) to a maximum of approximately 12 million residents (London, the densest FUA in the sample). The top 15 FUAs with the largest populations, which together represent well over 50% of the total population of the 53 metropolitan areas, include three Spanish FUAs (Madrid, Barcelona and Valencia), six German FUAs (Berlin, Hamburg, Munich, Frankfurt, Cologne and Essen), Dublin for Ireland, two Dutch FUAs (Amsterdam and Rotterdam) and two English FUAs, in addition to London, (Birmingham and Manchester).

TABLE 1 Selected characteristics of the Functional Urban Areas under research

Country	Number of metropolitan and large metropolitan FUAs	Resident population (2011) (A.V.)	Incidence of total population of selected FUAs (%)	Incidence on total resident population in country (%)
Germany	24	31,685,013	38.7	39.5
Ireland	1	1,690,947	2.1	36.9
Spain	8	16,744,726	20.5	35.8
The Netherlands	5	6,172,234	7.5	36.9
United Kingdom	15	25,538,350	31.2	40.3
Total	53	81,831,270	100.0	37.4

Source: OECD city and region data base.

TABLE 2 Multi-group residential segregation indices computed for the major FUAs of selected European countries: brief description, types and bibliographic references

Index	Description	Types	References
Information theory (H)	The multi-group version of Theil's entropy index (H Theil)	Disproportionality, association, diversity ratio	Theil, 1972; Theil & Finizza, 1971
Dissimilarity (D)	Multi-group dissimilarity index - a multi-group version of Duncan's dissimilarity index (D)	Disproportionality	Morgan, 1975; Sakoda, 1981
Normalized exposure (P)	Multi-group normalized exposure index - a multi-group version of the Bell's exposure index (xPy)	Weighted average	James, 1986
Squared Coefficient of Variation (C)	Can be interpreted as a measure of the variance of the spatial representation of the groups across spatial units, or as a normalized chi-squared measure of association between groups and units.	Disproportionality, association	Reardon & Firebaugh, 2002
Relative Diversity (R)	Multi-group relative diversity index - a multi-group index based on Simpson's interaction index (I)	Diversity ratio	Carlson, 1992; Goodman & Kruskal, 1954; Reardon, 1998

Source: authors' own work, based on Reardon and Firebaugh (2002).

MULTI-GROUP INDICES

The multi-group residential segregation indices used in this paper are listed and described in Table 2. The indices have been computed using the OasisR package (Tivadar, 2019). In some cases, they are an evolution of well-known two-group indices (in the case of D and P), while in other cases, they rely on other well-known indices (H and R) or, alternatively, they have been constructed directly as a multi-group measure (C). Each of them is calculated following a precise conceptual and mathematical approach to segregation, which makes it possible to highlight aspects of the phenomenon that can change radically from one context to another (Reardon & Firebaugh, 2002). European cities – identified here through a functional (gravitation) approach – do not in fact differ from one another only in terms of migration history, integration and housing policies and the foreign-born communities involved; they also vary in terms of urban morphology. As a matter of fact, compact and mono-centric settlements in Europe alternate with less dense and moderately polycentric urban systems (Benassi, Bonifazi, et al., 2020; Pili et al., 2017; Salvati & Serra, 2016).

As described in Reardon and Firebaugh (2002), each multi-group index is classifiable into basic types, in relation to how it addresses the issue of social segregation. These categories correspond to the approaches used here to derive multi-group indices. Following Reardon and Firebaugh (2002), there are basically four ways of viewing residential segregation, and, therefore, of measuring it through the indices derived from these approaches:

(i) Segregation as a function of non-proportionality (disproportionality) in the proportions of groups in elementary territorial units (Firebaugh, 1998, 1999; Reardon & Firebaugh, 2002).
(ii) Segregation as an association between population groups and elementary territorial units (Reardon & Firebaugh, 2002).
(iii) Segregation as variability in the diversity of units (e.g. variation in the composition of ethnic groups in a census section: Reardon & Firebaugh, 2002).
(iv) Segregation measured through indices that are constructed as weighted averages of dichotomous residential segregation indices (Reardon & Firebaugh, 2002).

With reference to these indices, in Table 2, we report details provided in Reardon and Firebaugh (2002), from which we have adopted the same notation to formalize the indicators. In particular, t denotes size and π denotes proportion; subscripts i and j index territorial units; and subscripts m and n index group. Hence, t_j = number of cases in territorial unit j; T = total number of cases; π_m = proportion in group m; π_{jm} = proportion in group m, of those in unit j.

The multi-group version of the Theil's entropy group index can be written as:

$$\mathbf{H} = \sum_{m=1}^{M} \sum_{j=1}^{J} \frac{t_j}{TE} \pi_{jm} \ln \frac{\pi_{jm}}{\pi_m} \tag{1}$$

The second index, the multi-group version of the Duncan's dissimilarity index, can be written as:

$$\mathbf{D} = \sum_{m=1}^{M} \sum_{j=1}^{J} \frac{t_j}{2TI} \left| \pi_{jm} - \pi_m \right| \tag{2}$$

The third index, the normalized exposure index is:

$$\mathbf{P} = \sum_{m=1}^{M} \sum_{j=1}^{J} \frac{t_j}{T} \frac{\left(\pi_{jm} - \pi_m\right)^2}{\left(1 - \pi_m\right)} \tag{3}$$

The last two indices are:

$$\mathbf{C} = \sum_{m=1}^{M} \sum_{j=1}^{J} \frac{t_j}{T} \frac{\left(\pi_{jm} - \pi_m\right)^2}{(M-1)\pi_m} \tag{4}$$

and

$$\mathbf{R} = \sum_{m=1}^{M} \sum_{j=1}^{J} \frac{t_j}{TI} \left(\pi_{jm} - \pi_m\right)^2 \tag{5}$$

In the above equations, E denotes Theil's Entropy Index (Theil, 1972) and I represents the Simpson's Interaction Index (Lieberson, 1969; White, 1986):

$$\mathbf{E} = \sum_{m=1}^{M} \pi_m \ln\left(\frac{1}{\pi_m}\right)$$

$$\mathbf{I} = \sum_{m=1}^{M} \pi_m (1 - \pi_m)$$

As Table 2 shows, belonging to a type of index is not a mutually exclusive condition. The meaning of the different indices is as follows:

- *Multi-group H* is the multi-group version of the popular entropy index H (Theil, 1972; Theil & Finizza, 1971) It is related to the dimension of *evenness* but, unlike D, it addresses the social diversity characterizing a given territory.
- *Multi-group D* is a multi-group version of the dissimilarity index of Duncan and Duncan (1955). From the theoretical point of view, this index belongs to the dimension of evenness (Massey & Denton, 1988) and measures the degree of dissimilarity that exists between different groups that reside simultaneously in a given territory.
- *Multi-group P* is derived from exposure indices (Bell, 1954; Farley, 1984). It indicates the degree of isolation (low exposure) that exists between groups, and is relative to the size of the exposure (isolation) according to the conceptual scheme produced by Massey and Denton (1988).
- *Multi-group C*, which is not derived directly from any bi-group index, was proposed by Reardon and Firebaugh (2002). It can be interpreted as *"as a measure of the variance of the $r_{jm's}$"* or *"as a normalized chi-squared measure of association between groups and units"* (Reardon & Firebaugh, 2002: 42).
- *Multi-group R*, assumed to be the equivalent of Goodman and Kruskal's τ_b (Reardon & Firebaugh, 2002), can be interpreted as *"one minus the ratio of the probability that two individuals from the same unit are members of different groups to the probability that any two individuals are members of different groups"* (Reardon & Firebaugh, 2002: 46).

From a mathematical (Reardon & Firebaugh, 2002) and operational (Lee et al., 2008) perspective, multi-group H index has the most desirable properties and gives the best performance in empirical terms. However, it should be remembered that the aim here is not so much to establish the goodness of fit as to understand their behaviour in different urban contexts, and to try to measure their reciprocal relationship and latent dimensions.

STATISTICAL ANALYSIS

We used a **M(c,v)** data matrix, where the cases (i.e. statistical units) were the 53 FUAs and the variables were the five multi-group segregation indices. The statistical analysis described in the following section aims to investigate the relationship between multi-group indices, evaluating a significant part of shared variability by extracting latent factors that reproduce the maximum part of the variability of the **M(c,v)** matrix (Di Feliciantonio et al., 2018; Gavalas et al., 2014; Morelli et al., 2014). To achieve this, we first calculated a series of linear correlation coefficients and then performed a principal component analysis (PCA). In addition, we aimed to understand the relationship between contextual (demographic and socio-economic) variables and multi-group segregation indices. In this regard, we used a synthesis of all the multi-group segregation measures to consider all the dimensions of segregation together. To do this, we introduced an *ad hoc* indicator based on Gismondi and Russo (2004) to summarize the loadings of the first two components extracted and assume the independence of the components by construction. The composite indicator is obtained in the following way:

1. Extracting the principal components from the statistical matrix **M(c,v)**;
2. Standardizing the *v* indices, taking into account the respective average (μ) and standard deviation (σ):

$$Z_v = \frac{v_i - \mu}{\sigma} \quad (6)$$

3. Computing the final index (PC index) for each FUA (i) as the weighted arithmetic mean of the standardized indicators (point 2), calculated using the coordinates of the factorial axes and the variance of the components derived from the PCA (point 1) as weights.

Formally, in the case of the two principal components, the *PC index* (point 3) is calculated as follows:

$$PC\ index_i = \frac{\lambda_I \sum_{v=1}^{V} z_{vi} a_{Iv} + \lambda_{II} \sum_{v=1}^{V} z_{vi} a_{IIv}}{\lambda_I + \lambda_{II}} \quad (7)$$

where *z* are the standardized indicators for each variable (i.e. multi-group segregation indices) *v* and territorial unit (FUA) *i*, *a* represents the coordinates of the factorial axes relative to the two principal components (I and II) and λ expresses the variance of the principal components. This method is based on uncorrelated factors and takes more than one component into account. Moreover, the weight of the variables in computing the PC index reflects the variance explained by each factor; in this way, the variables with higher component loadings have greater weights. The index obtained has been standardized by a linear transformation based on the equation:

$$PC\ index_i^* = \frac{PC\ Index_i - PC\ Index_{min}}{PC\ Index_{max} - PC\ Index_{min}} \quad (8)$$

thus producing elementary scores ranging between 0 and 1. The index was then used in relation to a key variable in the labour market (the unemployment rate) to shed lights on its behaviour.

RESULTS

Levels and types of multi-group residential segregation

Before presenting and discussing the results, it is useful to focus on the different composition in terms of foreign-born population that characterize each country analysed. Table 3 shows some basic population data from 2011.

There is a quite high level of heterogeneity between the countries selected here in terms of the size of the foreign-born population and the main foreign country of birth recorded in the 2011 census. The highest figure is from Ireland, where the foreign-born population accounts for about 17% of the total population, while the lowest (11.2%) is observed in The Netherlands. In Ireland, 72.3% of the foreign-born population came from other European Union countries. In The Netherlands, United Kingdom and Spain, the vast majority (between 65% and 75%) of the foreign-born population originated from outside the European Union. Germany showed an intermediate pattern, with those born outside the European Union slightly exceeding those born in another EU country. Turkey is one of the two main countries of birth both in Germany and in The Netherlands. Poland is the main country of birth in 3 countries: the United Kingdom, Ireland and Germany. In Spain, Morocco and Romania are

TABLE 3 Basic population data for the selected European countries in the analysis, 2011

Country	Population born abroad (A.V. in 1,000)	% of total population	EU27 (%)	Non-EU27 (%)[a]	Main Countries[(b)]
Germany	10,906	13.6	47.9	52.1	Poland, Turkey
Ireland	767	16.8	72.3	27.7	United Kingdom Poland
Spain	5649	12.1	33.5	66.5	Morocco, Romania
The Netherlands	1869	11.2	24.2	75.8	Turkey, Suriname
United Kingdom	7986	12.6	33.5	66.5	India, Poland

[a]Croatia was not yet an EU member country in 2011.

[b]Information on the main countries from The Netherlands is based on "Dutch Census 2011. Analysis and Methodology" Statistics Netherlands, The Hague/Heerlen 2014 and refers to top 10 immigrant groups in non-EU/EFTA countries by duration of stay, 2011 (p. 53).

Source: partially based on Benassi, Bonifazi, et al. (2020) on Eurostat 2011 Census Hub data.

the main foreign-born countries, while in the United Kingdom, it is India and Poland. Suriname is the second main foreign-born country in The Netherlands.

The intrinsic ranking of the first 30 FUAs for multi-group indices H, P, D, C and R is illustrated in Table 4, together with the descriptive statistics for each indicator. As can be seen, there is a clear distinction between the Spanish FUAs and the other European FUAs analysed here. The first group shows comparatively higher values of H, D, C and R, systematically occupying the highest positions in the ranking of these indices. For P, the situation is somewhat different, with Leicester coming first, and another two non-Spanish FUA, Bradford and Rotterdam in the top ten positions.

The FUAs of the other countries are relatively scattered in the ranking, with German cities ranking bottom, on average. In terms of the statistical distribution, we can observe how the min-max and mean values for D are comparatively high, especially compared to H, since they are two indices of the same dimension of segregation (evenness). The dimension of isolation (P) is relatively low in all the FUAs here analysed, as are the values delineating the statistical distribution of C and R.

The relationship between multi-group segregation indices and latent components

All multi-group indices present positive and a relatively high level of linear correlation (from 0.64 to 0.97). This means that all the indicators are biased in the same direction as regards the concept of residential segregation, and that there is a significant amount of common variance. This underlines the need for PCA, whose results are reported in Tables 5 and 6 and Figure 1.

The first two components account, together, for 0.97 of the initial variance (85% the first component and 12% the second). Component 1 alone accounts for about 0.85 of that variance and assigns positive loadings to all the multi-group indices analysed here. The highest loadings were assigned to H (0.458) and D (0.461). Based on loadings, component 1 can be seen as a latent dimension directly correlated with multi-group segregation (from comparatively low-to-negative values on the first axis of Figure 1 to comparatively high-to-positive values on the first axis in the same figure) and particularly in the dimension of evenness. The second component records both positive and negative component loadings. The highest positive correlation is recorded for P (0.672); the highest negative correlation is recorded for H (−0.386). This component is more closely related to the dimension of isolation, and diversity. From Figure 1, we can see clearly the difference between Spanish FUAs and the other urban agglomerations. German cities are clustered separately from the rest of continental cities in Europe, while Dutch and UK cities are more heterogeneous and substantially concentrated on positive values of both axes 1 and 2.

TABLE 4 Ranking of the top 30 FUAs. H, P, D, C and R

Ranking	*H*	Ranking	*P*	*Ranking*	*D*	*Ranking*	*C*	*Ranking*	*R*
Seville	0.6130	Leicester	0.1929	Seville	0.9498	Barcelona	0.1240	Zaragoza	0.1777
Bilbao	0.5426	Zaragoza	0.1817	Las Palmas	0.9114	Madrid	0.1188	Màlaga	0.1694
Valencia	0.5333	Màlaga	0.1764	Bilbao	0.9071	Màlaga	0.1041	Barcelona	0.1505
Las Palmas	0.5316	Bradford	0.1590	Valencia	0.8549	Zaragoza	0.1041	Madrid	0.1501
Màlaga	0.5255	Madrid	0.1582	Màlaga	0.8404	Valencia	0.1026	Leicester	0.1498
Barcelona	0.5191	Barcelona	0.1534	Barcelona	0.8005	Seville	0.0953	Valencia	0.1366
Zaragoza	0.4841	Sheffield	0.1494	Zaragoza	0.7989	Bilbao	0.0901	Seville	0.1364
Madrid	0.4818	Seville	0.1417	Madrid	0.7660	Las Palmas	0.0885	Bradford	0.1295
Amsterdam	0.2565	Rotterdam	0.1414	Sheffield	0.5135	Eindhoven	0.0540	Sheffield	0.1160
Sheffield	0.2531	Valencia	0.1403	Bradford	0.5074	Dublin	0.0514	Bilbao	0.1147
Rotterdam	0.2468	Birmingham	0.1328	Leicester	0.5007	Essen	0.0458	Rotterdam	0.1076
The Hague	0.2429	London	0.1239	New Castle	0.4762	Bochum	0.0441	Birmingham	0.1042
Glasgow	0.2359	The Hague	0.1209	Birmingham	0.4730	Glasgow	0.0429	London	0.1019
Leicester	0.2341	Amsterdam	0.1192	Rotterdam	0.4726	London	0.0427	Las Palmas	0.1015
Saarbrücken	0.2336	Manchester	0.1189	Leeds	0.4718	Amsterdam	0.0401	The Hague	0.0987
Bradford	0.2327	Bilbao	0.1157	Saarbrücken	0.4662	The Hague	0.0386	Amsterdam	0.0977
New Castle	0.2302	Leeds	0.1112	Glasgow	0.4640	Leicester	0.0376	Manchester	0.0904
Eindhoven	0.2286	Las Palmas	0.1105	Manchester	0.4523	Augsburg	0.0370	Dublin	0.0882
Leeds	0.2238	Glasgow	0.1096	Liverpool	0.4519	Sheffield	0.0368	Glasgow	0.0879
Birmingham	0.2225	New Castle	0.1080	Nottingham	0.4497	Hamburg	0.0368	Leeds	0.0851
Liverpool	0.2153	Nottingham	0.1053	Amsterdam	0.4367	Duisburg	0.0367	Liverpool	0.0808
Essen	0.2151	Augsburg	0.1027	Cardiff	0.4338	Leipzig	0.0362	New Castle	0.0781
Freiburg	0.2151	Dublin	0.1020	Nuremberg	0.4278	Utrecht	0.0359	Nottingham	0.0778
Utrecht	0.2144	Liverpool	0.1012	Augsburg	0.4271	Edinburgh	0.0358	Eindhoven	0.0774
Manchester	0.2135	Nuremberg	0.0937	Freiburg	0.4271	Birmingham	0.0353	Edinburgh	0.0735

(Continues)

TABLE 4 (Continued)

Ranking	*H*	Ranking	*P*	*Ranking*	*D*	*Ranking*	*C*	*Ranking*	*R*
London	0.2064	Freiburg	0.0936	Eindhoven	0.4211	Munich	0.0350	Augsburg	0.0732
Nottingham	0.2031	Cardiff	0.0929	The Hague	0.4203	Bradford	0.0342	Utrecht	0.0731
Augsburg	0.2006	Eindhoven	0.0906	London	0.4195	Manchester	0.0339	Cardiff	0.0705
Munster	0.2002	Utrecht	0.0905	Edinburgh	0.4138	Leeds	0.0331	Freiburg	0.0688
Frankfurt	0.1993	Edinburgh	0.0889	Munster	0.4106	Bremen	0.0329	Essen	0.0685
Min	0.12	Min	0.04	Min	0.31	Min	0.01	Min	0.03
Max	0.61	Max	0.19	Max	0.95	Max	0.12	Max	0.18
Mean	0.25	Mean	0.10	Mean	0.48	Mean	0.04	Mean	0.08
Sd	0.12	Sd	0.04	Sd	0.17	Sd	0.03	Sd	0.04
CV	49.19	CV	35.07	CV	35.28	CV	66.82	CV	42.36
N	53	*N*	53	*N*	53	*N*	53	*N*	53

Source: authors' own work based on D4I data.

TABLE 5 Analysis of the eigenvalues of the correlation matrix

Factors	Eigen value	Proportion	Cumulate
1	4.2348	0.8470	0.8470
2	0.6161	0.1232	**0.9702**
3	0.1343	0.0269	0.9970
4	0.0094	0.0019	0.9989
5	0.0055	0.0011	1.0000

Source: authors' own work based on D4I data.

TABLE 6 Component loadings

Multigroup segregation indices	1st comp	2nd comp	3rd comp	4th comp	5th comp
H	0.458	−0.386	−0.317	0.644	0.353
P	0.412	0.672	−0.104	−0.245	0.555
D	0.461	−0.320	−0.490	−0.592	−0.309
C	0.447	−0.332	0.795	−0.199	0.133
R	0.456	0.431	0.129	0.368	−0.674

Source: authors' own work based on D4I data.

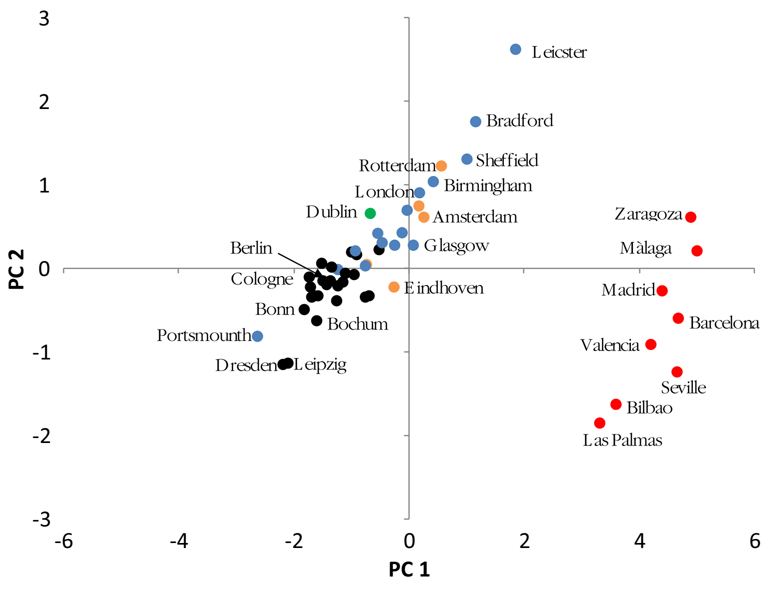

FIGURE 1 Factorial plane and statistical units[a].
Source: Authors' own work based on D4I data. (a) Red: Spain, blue: UK, orange: The Netherlands, black: Germany, green: Ireland

PC index and inequalities in the labour market

The PC index allows us to create a unique ranking of all the FUAs here analysed. We can rank the FUAs (Figure 2) from the one in which the multi-group segregation is the highest (PC index = 1.0, Málaga) to the one in which the multi-group segregation is the lowest (PC index = 0.0, Portsmouth). It should be noted that here the meaning of

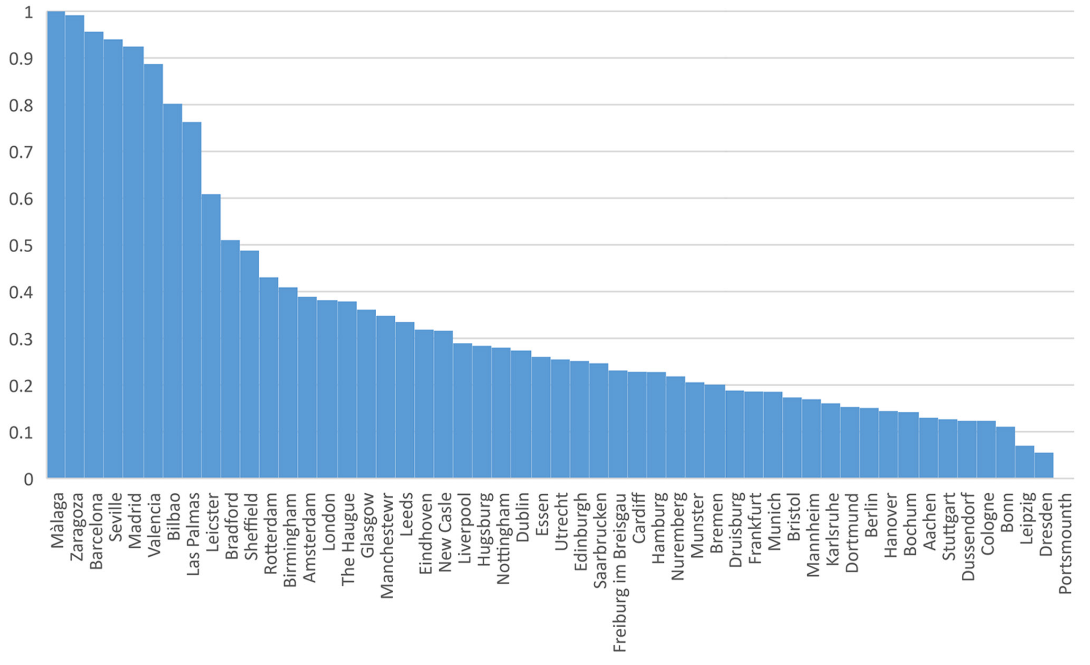

FIGURE 2 PC index (standardized). Selected FUAs.
Source: Authors' own work based on D4I data

"highest" and "lowest" refers to the empirical distribution of PC index based on the standardized version of the index (Equation 8). The distinction between Spanish FUAs and the other FUAs is evident. Only 10 FUAs record a standardized PC index value over 0.5: all the 8 Spanish FUAs plus two UK FUAs (Leicester and Bradford). In terms of statistical distribution, the standardized PC index has a mean value of 0.35, a median value of 0.25 and a coefficient of variation of 76.3%.

In this perspective, it is clear that the Spanish FUAs, belonging to Southern Europe, and all the other FUAs analysed here, belonging to Central and Northern Europe, differ greatly. These two 'blocks'—that is, two areas within the same main economic areas—are characterized by different levels of economic development and wealth and by different dynamics of the labour market. Typically, the level of unemployment is much higher in Southern Europe compared with Northern Europe. Moreover, the economies of the former are characterized by a comparatively high level of informal sector dynamics and low labour productivity.

One way to test whether the PC index behaviour is coherent with this evidence is to compare its distribution with the unemployment rate in the FUAs here selected. The results are clear (Figure 3): the relationship between the unemployment rate and PC index in the selected FUAs – that is, between unemployment and multi-group segregation – is positive, with a linear correlation coefficient of 0.81. In metropolitan contexts where the unemployment rate is low, the PC index of multi-group segregation is low, and the opposite holds for contexts with high unemployment rates.

DISCUSSION

As Piketty recently argued (Piketty, 2020), in an increasingly unequal society, where accumulation has become the key to the social system, we can consider the residential market and all its social dimensions as one of the variables that best reflects the growing inequalities and inconsistencies of the neoliberal economic model. In

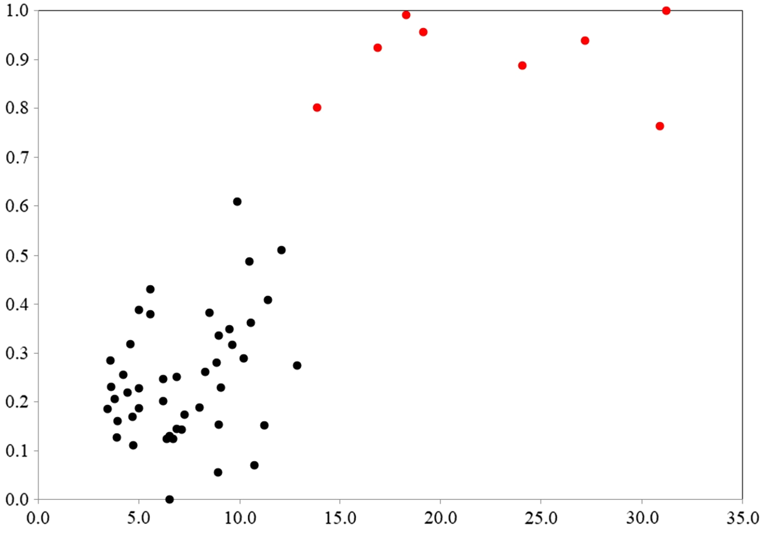

FIGURE 3 Scatterplot between PC index standardized (y axe), and unemployment rate as a share of labour force (%). 2011[a].
Source: authors' own work based on D4I data and on data from OECD city and region data base. [a]Red: Spanish FUAs. y = 0.0333x + 0.0284; $R^2 = 0.66$; $r = +0.81$ (for all FUAs). y = 0.0159x+0.132; $R^2 = 0.10$; $r = +0.33$ (for non-Spanish FUAs)

this context, given the growing ethnic and cultural diversity of European societies, it is more necessary than ever to generate flexible and useful tools to analyse processes of integration and segregation in the foreign population (Auspurg et al., 2017) to develop effective policies to build a more cohesive European society (Piekut et al., 2019).

Based on these assumptions, our study set out to answer two main research issues: (i) first, from a methodological/technical point of view, we looked at the validity and interrelation of the multi-group indices for analysing segregation patterns and (ii) second, from a socio-territorial approach, we tested the usefulness of these indices when relating them to the main social variables that account for segregation. In this perspective, our study includes, for the first time as far as we know, an in-depth reflection about multi-group segregation levels using comparative data, functional and standardized geographies (Functional Urban Areas) and a unique indicator (PC index) that summarizes several dimensions of multi-group segregation simultaneously.

From a methodological point of view, the empirical results of this study provide new evidence for analysing residential segregation in multi-ethnic settings. We can see how H and D, as indices that show the uniformity and disproportionality of the groups analysed, are the most suitable scales for measuring the degree of diversity in today's multi-ethnic societies. We can therefore consider them of special importance when analysing the degree of ethnic diversity of a society and its territorial impact. It is also a valid socio-territorial indicator to relate to other socio-economic variables, and allows us to arrive at a better diagnosis of the levels of socio-territorial cohesion. In turn, similar values of P and R reflect their contribution to the analysis of the potential social interaction of the foreign population with the native population. The P and R indices, by estimating the possibility of sharing common spaces, can therefore play a fundamental role in helping us to understand the spatial dimension of interethnic relations, as different theoretical approaches have shown (e.g. Allport, 1954; Blalock, 1967; Iglesias-Pascual et al., 2019).

The analysis of the relationship of multi-group segregation indices with social variables shows how a comprehensive understanding of urban segregation is only possible if they are intended as a spatial result of (urban) inequalities (van Ham et al., 2021). Our macro-scale findings, in line with recent studies at a micro-local level (Marcińczak et al., 2021), show that segregation is higher in the urban areas of Europe with a less stable economy and a high level of social vulnerability (e.g. Spain) than in its Central and Northern counterparts. Intense multi-group segregation in Spanish metropolitan areas, an aspect that has already been partially analysed (Benassi, Iglesias-Pascual, et al., 2020), confirms the importance of carrying out a comparative analysis of the real estate markets in each country. In areas of growing multi-culturalism and greater social vulnerability, a relevant aspect that deserves further investigation is the inherent difficulty for migrants to access the housing market (Farley et al., 2000; Iglesias-Pascual, 2019; Van der Bracht et al., 2015).

Moreover, intense multi-group segregation allows us to relativize the idea that Spanish attitudes towards immigration have been an exception within Europe (Rinken and Trujillo-Carmona, 2018). In fact, so far, there have been no major social reactions against migrants, nor can the recent rise of the extreme right in Spain be linked to the presence of a migrant population as clearly as in other European countries (Iglesias-Pascual et al., 2021). However, it is evident that these high values of residential segregation can be understood as a sign of the low degree of prejudice felt by the Spanish population towards their migrant population.

One clear indication of this emerges from the analysis of the PC index in relation to unemployment: the higher the unemployment rate, the higher the PC index values. Many recent studies have gained important insights into the relationship between urban segregation and economic inequalities (van Ham et al., 2021) and the importance of the labour market in defining residential segregation (Benassi, Bonifazi, et al., 2020). Conversely, when the unemployment rate is low, multi-group segregation is low. The vicious circle of marginality has been clearly highlighted in a recent study (Benassi, Iglesias-Pascual, et al., 2020). This evidence demonstrates how multi-group segregation rates increase in contexts of high unemployment, with more saturated housing markets in places where migrants are more segregated, due to the greater difficulty in accessing housing.

CONCLUSION

Our results indicate how, to reduce the level of urban segregation, it is necessary to reduce inequalities between urban Europe in terms of unemployment and to help local public institutions to develop more active housing policies that do not leave housing management exclusively in the hands of the real estate market. As we have seen since the economic crisis of 2008, the housing market seeks efficiency and profit, not social equity. By reshaping the foundations for inclusive societies and more cohesive local contexts, new forms of active intervention are needed to reduce social segregation and economic divides. The current pandemic, naturally poses an added health threat as well as socio-economic inequalities. It would not be reckless to assume that these effects are greater in the most fragile and, above all, less socially cohesive contexts, affecting especially the most vulnerable populations. New avenues for research are also opening up on the basis of our results, which we hope can be followed. On the one hand, the current census round will produce new population counts, also in relation to foreigners. These new data, if processed and made available on regular grids consistent with those used in the study, may provide an opportunity to assess the spatial and temporal evolution of the level of residential segregation in European metropolitan areas. On the other hand, hopefully, the recovery of the economy thanks in part to the post-pandemic investment plans will lead to a recovery in the labour markets, which could in turn result in lower unemployment rates and a corresponding decrease in the level of multi-group residential segregation, given the negative correlation between the two quantities. To be able to design spatially and territorially appropriate policies, it is therefore necessary to invest in refined population statistics based on regular grids.

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CONFLICT OF INTEREST

None.

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ENDNOTES

1. Information about the D4I Data Challenge is available on the following link: https://blue ub.jrc.ec.europ a.eu/ datachallenge/. The main results are published in Tintori et al., 2018.
2. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_grids#Grid_statistics
3. Not applicable to Portugal, as information is only available at a continental level.

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