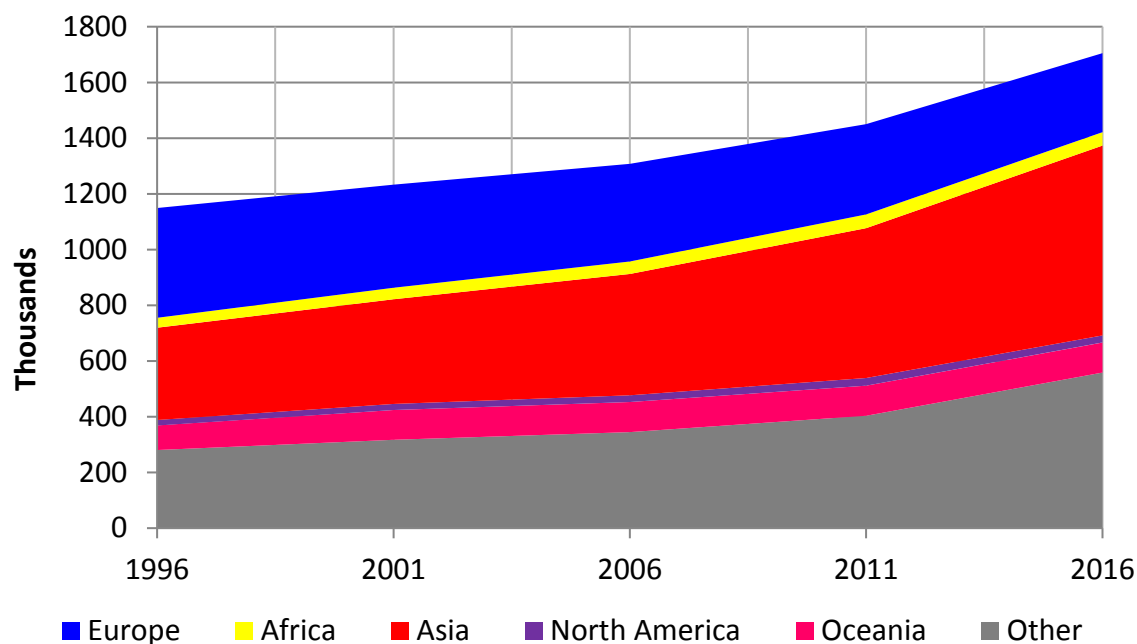


# Spatial Incorporation of Multiple Immigrant Groups in Gateway Cities: Comparative Analysis of Sydney, Barcelona, and Prague - Online Appendix

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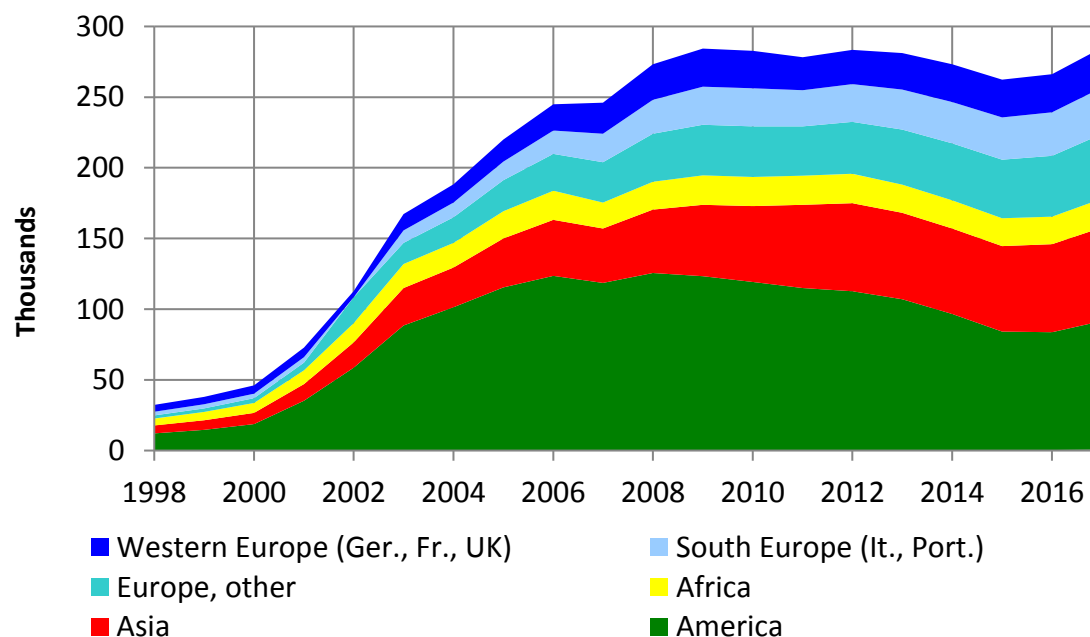
## A1. Destination cities

**Figure A1.** Main regions of birth of immigrant groups in Sydney, 1996-2016.



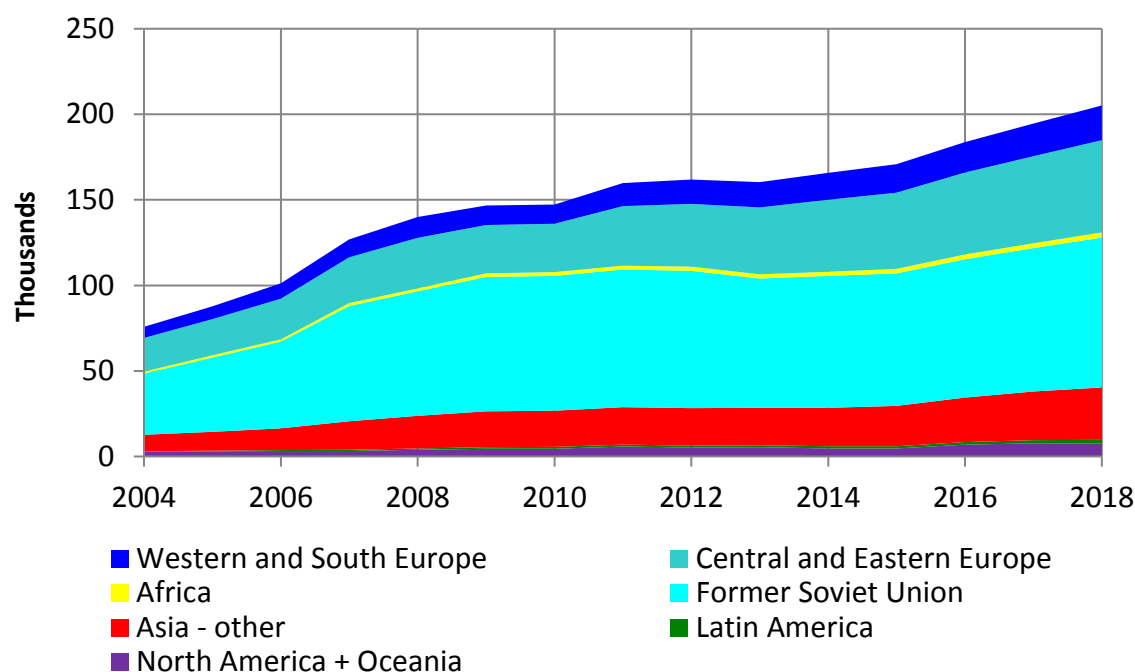
Source: Australian Bureau of Statistics

**Figure A2.** Main regions of citizenship of immigrant groups in Barcelona, 1998-2017.



Source: Instituto Nacional de Estadística

**Figure A3.** Main regions of citizenship of immigrant groups in Prague, 2004-2018.



Source: Czech Statistical Office, Alien Police

## A2. Data and methods

### A2.1 Data

We analysed the most up-to-date and comparable data from the three studied cities on the number of immigrants based on their country of origin. Census data from 2016 (defined by country of birth) were used for Sydney, while data from continuous population registers (defined by country of citizenship) were used for Barcelona (from 1/1/2017) and Prague (from 31/12/2015). Notably, the difference between both definitions of country of origin should not influence our results since each city was analysed separately. Moreover, Hasman and Novotný (2017) showed that the spatial patterns observed when using migrants' citizenship and country of birth data were very similar.

Important decisions were made regarding (1) the scale of analysis and (2) the number and size of immigration groups analysed.<sup>1</sup> Concerning the former decision, some spatial analysis methods (e.g. spatial autocorrelation) require very detailed data. However, since the structure of administrative units in each city is very different, we could not obtain fully comparable data across cities. While the Census sections selected for Barcelona and the Basic settlement units for Prague are similar, smaller Statistical areas level 1 units were selected for Sydney as Statistical areas level 2 units with a mean population size of 15,752 would have been too

<sup>1</sup> The term "immigration group" refers to the set of all immigrants with the same country (or region) of origin.

large. Since this choice corresponds to higher proportions of immigrants in Sydney, the number of immigrants (and thus the possibility of detecting spatial patterns) is comparable to that of the other two cities. Unpopulated units (234 in Sydney and 160 in Prague) were excluded from the analysis. Further details regarding the selected spatial units (hereafter “localities”) can be found in Table A1.

**Table A1.** Basic characteristics of the administrative units used in the analyses of immigration groups’ spatial distribution.

	Sydney	Barcelona	Prague
Number of locations	9,753	1,068	758
Total population	4,221,411	1,620,809	1,267,246
Mean population size	433	1,518	1,672
Immigrant population (%)	43.6	17.6	13.3
Immigrant population per location	189	267	222

Source: Australian Bureau of Statistics, Czech Statistical Office, Instituto Nacional de Estadística.

Another important issue involved deciding the size of immigrant groups to be included in the analysis. Notably, the analysis of very small groups may be problematic due to the larger role of random oscillations, the risk of which can be even greater since data from the Australian and Spanish statistical offices are deliberately inaccurate to ensure confidentiality. On the other hand, we aimed to include as many groups as possible to obtain the maximum amount of information and achieve the most complex pattern possible (which is also desirable for methods such as spatial relatedness). Thus, we chose a more inclusive approach and merged only the smallest groups (below 100 members) to regional aggregates in the case of Sydney (resulting in a total of 143 groups, including the domestic population) and below 70 members in the case of Prague (resulting in 95 groups), while larger groups were maintained. Since the data for Barcelona were divided into only 54 countries/regions of birth, all groups were retained.

Although the inclusion of small groups may be disputable, we believe that our findings may give rise to recommendations for future research in terms of the appropriate group size for such quantitative analyses. Moreover, their inclusion can bring added value when compared to many existing studies that were limited to only a few selected groups and thus ignored the complexity of destination societies provided by the presence of multiple groups (Alba and Nee 1997). Furthermore, it should be useful in determining which group could bring useful information. Additionally, the inclusion of most groups may be beneficial for further case studies of these groups by providing basic information about their spatial patterns. However,

the inclusion of small groups should be considered when interpreting our results. We also had to adjust our methods to minimise the potential bias caused by these small groups.

To evaluate the role of generational change in immigrant incorporation highlighted by assimilation theories (Alba and Nee 1997), we adopted an alternative approach to the longitudinal and cohort analyses most frequently used in the incorporation literature. Since data on the residential distribution of immigrant group generations in all three cities were unavailable, we collected data on the proportion of the population (excluding children up to 10 years) residing in each destination city for over 10 years for each immigrant group. We employed the most up-to-date data from the most recent censuses (2016 for Sydney and 2011 for Barcelona)<sup>2</sup> and the population register for Prague (Table A2)<sup>3</sup>.

**Table A2.** Descriptive statistics of the length of stay indicator

City	Mean	Standard deviation	Minimum	Maximum
Sydney	0.669	0.194	0.059	0.989
Barcelona	0.274	0.177	0.000	1.000
Prague	0.206	0.123	0.000	0.505

To display destination cities' spatial-economic segmentation, we created one map for each city. Since these maps intended to show only the basic features of the cities' structures, comparable data were not required and we utilised the most illustrative available data. For Sydney, we used mean personal income in Statistical areas level 2 units from the 2016 census (larger spatial units were more appropriate since a map for Statistical areas level 1 would be too fragmented). In the case of Barcelona, we used the average sales price of houses (by neighbourhood) in 2016 (Barcelona 2019). For Prague, data for building plots in Basic settlement units in 2015 were mapped (Praha 2018).

## A2.2 Methods

Given the supposed multidimensionality of spatial incorporation, we decided to measure the two dimensions that we considered most important for our paper: evenness and clustering (as defined by Massey and Denton 1988). Evenness measures the concentration of immigrant group members in localities (regardless of their location). Since the level of incorporation is

<sup>2</sup> Although a time gap exists between the census for Barcelona and the date of the population register data on immigrants' spatial patterns, we believe that the data are stable in time and that such a time gap should not affect our results.

<sup>3</sup> Due to a lack of alternative data, the indicator for Prague was calculated as the proportion of the given immigrant group residing in Prague in 2015 whose resident permit was issued in 2005 and who also resided in the Czech Republic in 2008.

highly scale-dependent (Johnston et al. 2016) and we used very detailed data, we can capture evenness at the finest level. Conversely, clustering quantifies whether members cluster together in localities with an overrepresentation of an immigrant group; thus, it can detect concentration at a higher spatial level.<sup>4</sup> Thus, both measures may—but do not have to—be correlated.

Measures of evenness are numerous and highly intercorrelated (Massey and Denton 1988). Table A3, which presents the Pearson’s correlations between two classical measures (the Gini coefficient and index of dissimilarity) and one alternative ( $D_{i,j}$ , see below) measure of evenness, confirms that such high correlations also occurred within our data. However, all of these measures are also extremely correlated with group size.<sup>5</sup> This issue—often neglected in the segregation literature—is even more severe in our case since we also analysed small groups whose spatial distribution must be highly uneven because they can only live in a few localities (Manley, Jones, and Johnston 2019). Thus, we have thus taken this dependence into account as follows. For each group  $i$ , we have calculated the Gini coefficient (which is less correlated with group size than the more common index of dissimilarity) weighted by the population size of localities:

$$G_i = \frac{1}{2Y_i} \sum_{l=1}^n \sum_{m=1}^n \left( \frac{x_l x_m}{X} |y_{i,l} - y_{i,m}| \right), \quad (1)$$

where  $n$  denotes the number of localities,  $y_{i,l}$  and  $y_{i,m}$  are the proportions of group  $i$  in the populations in localities  $l$  and  $m$ ,  $Y_i$  is the total population of group  $i$  in the city, and  $x_l$  and  $x_m$  are the proportions of the total populations in localities  $l$  and  $m$  relative to the total population in city  $X$ . The minimum value of the Gini coefficient is 0, meaning absolute evenness ( $y_i$  being the same across localities), and its maximum value is 1, representing absolute unevenness (all members of a group are concentrated in only one locality). To remove the influence of group size on the Gini coefficient, we used a regression analysis to model the relationship between the Gini coefficient and group size for each city. A quadratic function was the most appropriate for Sydney ( $R^2 = 88.0\%$ ) and a linear function was most appropriate for the other cities ( $R^2 = 77.6\%$  for Barcelona and  $86.0\%$  for Prague). For each group in each city, we then computed the differences between the original values of the Gini coefficient and the values predicted by the regression model. These residuals ( $RG_i$ ) allowed us to determine

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<sup>4</sup> Another way how we could have analysed spatial concentration on more spatial levels would be to use data on more spatial scales. However, suitable data were not available for Prague and Barcelona.

<sup>5</sup> Since the group size distributions were highly skewed in all cities, we used their logarithms in our analyses.

the real evenness of group  $i$  independent of its representation in a city. Positive values imply that group members are more concentrated than would be expected based on their group size, while negative values signal their greater dispersion. For simplicity (and to have the same interpretation as the clustering measure),  $RG_i$  is considered an indicator of unevenness (rather than evenness) in the present study.

**Table A3.** Pearson correlations for population size, evenness, and clustering measures

	Prague						
	Group size	log10 (Group size)	Gini coefficient	Index of dissimilarity	$D_{i,j}$	$RG_i$	Moran's I
Group size	.	0.659	-0.629	-0.530	0.269	-0.056	0.048
log10 (group size)	0.620	.	-0.906	-0.916	0.625	0.031	0.166
Gini coefficient	-0.790	-0.830	.	0.976	-0.751	0.396	-0.040
Index of dissimilarity	-0.742	-0.868	0.986	.	-0.934	0.342	-0.673
$D_{i,j}$	0.520	0.776	-0.897	-0.813	.	-0.462	0.070
$RG_i$	-0.104	-0.018	0.428	0.318	-0.419	.	0.266
Moran's I	0.495	0.820	-0.590	-0.080	0.564	0.369	.

Source: Authors' calculations

Note: Values denote the extent of the Pearson correlations computed for Sydney (below diagonal) and Prague data separately. Correlations for Barcelona (not shown) are generally similar to those of Sydney.

To assess the degree of clustering, we calculated Moran's I, which is (for its simple interpretation similar to Pearson's correlation coefficient) one of the most widely used indicators of spatial autocorrelation (Cliff and Ord 1973). Its value is bounded between -1 and 1. Positive values denote the clustering of localities with a high share of group  $i$ , while negative values correspond to a situation (albeit improbable) in which localities with a high share are adjacent to localities with a low share. Finally, values near zero imply the absence of a spatial pattern in the distribution of group  $i$  across localities. Moran's I for group  $i$  is computed as follows (Netrdová and Nosek 2009):

$$I_i = \frac{n \sum_{l=1}^n \sum_{m=1}^n w_{l,m} (y_{i,l} - y_i)(y_{i,m} - y_i)}{\sum_{l=1}^n \sum_{m=1}^n w_{l,m} \sum_{l=1}^n (y_{i,l} - y_i)^2}, \quad (2)$$

where  $y_i$  denotes the mean share of group  $i$  in the whole city and  $w_{l,m}$  corresponds to the weighting matrix, which defines neighbouring localities. Since the choice of weighting matrix may influence the resulting values of I, we tested several possibilities before finding the most appropriate solution for each city (the best choice differs between cities due to the different

spatial structures of their administrative units). As a result, we selected a 10-nearest-neighbour matrix for Sydney, rook contiguity for Barcelona (also used by Martori, Hoberg, and Suriñach 2005) and a constant distance of 2 km for Prague.<sup>6</sup>

Pearson correlations indicate a moderate relationship between clustering measure  $I_i$  and unevenness measure  $RG_i$  (0.37 for Sydney and 0.27 for both Barcelona and Prague), confirming that both assess different aspects of segregation. Moreover,  $I_i$  (like the Gini coefficient) is highly correlated with group size (Table A3). However, following additional inspections, we decided not to compute residual values since the relationship with group size was not as straightforward as in the case of the Gini coefficient. Although small groups typically have a small  $I_i$ , larger groups can have both a very high and a very low  $I_i$ ; therefore, we could not identify a function that would adequately describe the relationship between  $I_i$  and group size. Moreover, there was no relationship in the case of Prague since  $I_i$  was very low for most groups.

To test a possible spatial aspect of the segmented assimilation theory, we evaluated whether (and to what extent) different groups were concentrated in different localities by considering the location of such concentrations and the groups' length of stay in each destination city. We computed the symmetric Dice coefficient  $D_{i,j}$ , which measures the so-called spatial relatedness of two immigrant groups. It corresponds to the probability that one group is concentrated in a locality in which a second group is also concentrated (Novotný and Hasman 2015). Local concentration  $LQ_{i,l}$  is defined as  $y_{i,l}/y_i$ . Thus, we state that a group is concentrated in a locality when its  $LQ_{i,l}$  is higher than 1 (i.e. its relative representation in the locality is higher than in the entire city).  $D_{i,j}$  is then defined as the lower of the two asymmetric Dice coefficients:

$$D_{i,j} = \min\left(\frac{|\{l: LQ_{i,l} > 1\} \cap \{l: LQ_{j,l} > 1\}|}{|\{l: LQ_{j,l} > 1\}|}, \frac{|\{l: LQ_{i,l} > 1\} \cap \{l: LQ_{j,l} > 1\}|}{|\{l: LQ_{i,l} > 1\}|}\right), \quad (3)$$

where  $\{l: LQ_{i,l} > 1\}$  is the number of localities in which  $LQ_{i,l} > 1$  and the term  $|\{l: LQ_{i,l} > 1\} \cap \{l: LQ_{j,l} > 1\}|$  thus corresponds to the number of localities where both groups  $i$  and  $j$  are concentrated simultaneously (for a further discussion, see Hasman and Novotný 2018; Novotný and Hasman 2015). In contrast to the index of dissimilarity, which can also compare

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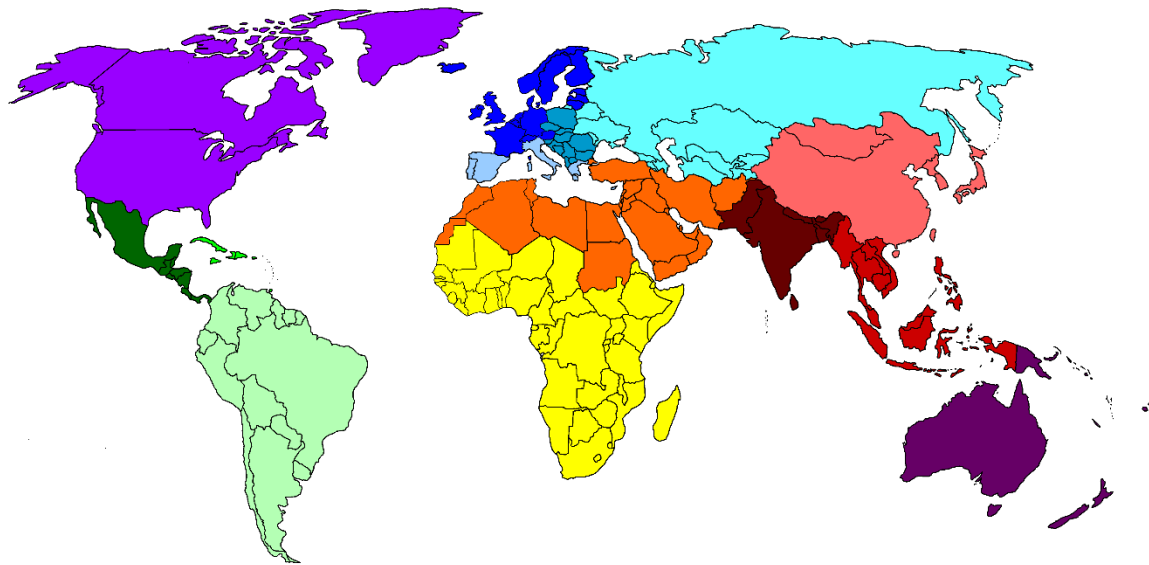
<sup>6</sup> Different schemas would lead to nearly the same results as Pearson correlations between several of the most appropriate schemas were approximately 0.99 for Sydney and Barcelona and approximately 0.98 for Prague.

the spatial distribution of two groups,  $D_{ij}$  is much less dependent on group size, which makes it a more appropriate measure of evenness (see Table A3).

$D_{ij}$  values were used to visualise the patterns of the spatial structure of immigrant groups in each city as an undirected network, where nodes represent particular groups and edges refer to the spatial relatedness between groups. Groups are coloured by their region (Figure A4) and labelled by acronyms corresponding (when possible) to ISO country codes. Node sizes correspond to the square root of groups' population size and shape in the proportion of immigrants with a length of stay greater than 10 years. Groups with this proportion above 80% are denoted by a circle, while those with 60–79.9% by an octagon, 40–59.9% by a hexagon, 20–39.9% by square and those below 20% by a triangle. The network visualisation was constructed using an edge-weighted spring-embedded algorithm, with the weights being linearly proportional to the values of  $D_{ij}$ . Such a network can be considered analogous to a physical system in which nodes (immigrant groups) attract each other by forces proportional to their pairwise relatedness ( $D_{ij}$ ). The algorithm minimises the energy of the physical system and accordingly assigns positions in two-dimensional space to the nodes. Since the lowest  $D_{ij}$  values can be affected by the random co-occurrences of immigrants, only edges above the given bound were considered for creating the visualisation network. This bound differed for each city depending on its spatial pattern (0.05 in Sydney, 0.34 in Barcelona, and 0.333 in Prague) and was specified by testing several values. However, different bounds would not affect the general view of visualisations. Moreover, only the strongest edges (above 0.2, 0.45, and 0.43 for Sydney, Barcelona, and Prague, respectively) were displayed to maintain a readable visualisation.

**Figure A4.** Regional division of countries





The visualisations enabled us to comprehensively evaluate the patterns of the spatial structure of immigrant groups in each city to determine which groups may have mutually different spatial distributions (and be segmented to different parts of a city). The spatial distributions of such groups were ultimately compared using map outputs obtained from the LISA analysis (Anselin 1995). LISA (Local Indicators of Spatial Association) is a local equivalent of the “global” Moran’s I that discovers clusters of localities with a high (or low) representation of a given group.

### A3. Supplementary data

**Table A4.** Main characteristics of population groups in Sydney, Barcelona, and Prague

Name of group	Acronym	Region	Sydney				Barcelona				Prague			
			Group size	Unevenness (RGi)	Clustering (Moran I)	Before 2001 (%)	Group size	Unevenness (RGi)	Clustering (Moran I)	Before 2006 (%)	Group size	Unevenness (RGi)	Clustering (Moran I)	Before 2001 (%)
Afghanistan	AFG	Middle East and North Africa	11,733	0.068	0.593	52.4	.	.	.	.	185	0.080	0.000	23.8
Africa, other	Afr	Sub-Saharan Africa	.	.	.	.	3,604	-0.012	0.299	38.2	.	.	.	.
Albania	ALB	Central and Eastern Europe	123	0.006	-0.002	54.1	.	.	.	.	158	0.000	-0.001	11.3
Algeria	DZA	Middle East and North Africa	314	-0.006	0.090	74.9	1,733	0.165	0.195	64.7	386	-0.069	0.013	40.0
America, other	Ame	South America	.	.	.	.	21,198	-0.115	0.540	25.3	.	.	.	.
Argentina	ARG	South America	3,684	-0.008	0.068	80.2	6,076	-0.078	0.351	25.7	79	-0.014	0.016	20.3
Armenia	ARM	Former Soviet Union	429	-0.006	0.077	78.7	.	.	.	.	802	0.001	0.000	21.1
Asia, other	Asi	Eastern Asia	.	.	.	.	27,013	0.085	0.794	25.3	11	-0.096	-0.001	27.3
Australia	AUS	Oceania	2,380,213	0.032	0.598	.	.	.	.	.	274	-0.012	0.061	29.5
Austria	AUT	Western Europe	1,140	-0.006	0.084	91.2	722	0.007	0.287	30.4	640	0.006	-0.002	50.6
Azerbaijan	AZE	Former Soviet Union	.	.	.	.	.	.	.	.	620	0.041	-0.006	3.9
Bahrain	BHR	Middle East and North Africa	128	0.005	0.005	59.2	.	.	.	.	.	.	.	.
Bangladesh	BGD	South Asia	22,240	0.085	0.706	44.5	.	.	.	.	97	0.044	-0.002	9.3
Belarus	BLR	Former Soviet Union	190	-0.003	0.000	56.3	.	.	.	.	2,137	-0.084	0.011	10.3
Belgium	BEL	Western Europe	526	-0.007	0.015	61.9	1,537	0.001	0.319	51.2	282	0.042	0.087	20.1
Bhutan	BTN	South Asia	297	-0.004	0.085	5.9	.	.	.	.	.	.	.	.
Bolivia	BOL	South America	231	-0.002	0.026	85.5	9,024	-0.019	0.451	5.5	.	.	.	.
Bosnia and Herzegovina	BIH	Central and Eastern Europe	5,145	0.005	0.296	95.2	.	.	.	.	915	-0.022	0.000	43.0
Brazil	BRA	South America	10,148	0.027	0.399	23.7	6,339	-0.149	0.347	19.6	212	-0.052	0.033	11.8
Brunei	BRN	South-East Asia	180	0.001	0.074	65.5	.	.	.	.	.	.	.	.
Bulgaria	BGR	Central and Eastern Europe	495	-0.007	0.022	67.9	1,930	0.088	0.131	15.8	3,892	-0.088	-0.006	18.8
Burma	MMR	South-East Asia	5,147	0.025	0.399	53.3	.	.	.	.	.	.	.	.
Cambodia	KHM	South-East Asia	11,035	0.082	0.598	80.2	.	.	.	.	.	.	.	.
Canada	CAN	North America	6,561	-0.026	0.155	62.7	.	.	.	.	443	-0.006	0.017	25.5
Caribbean, other	Car	Caribbean	226	-0.003	0.000	75.0	.	.	.	.	30	-0.055	-0.008	30.0
Central America, other	CAm	Central America	135	0.004	-0.003	66.4	.	.	.	.	108	-0.029	0.010	11.9
Central and West Africa, other	CWA	Sub-Saharan Africa	192	-0.002	0.003	56.6	.	.	.	.	354	-0.085	0.039	22.4
Colombia	COL	South America	4,942	-0.005	0.155	36.4	9,004	-0.213	0.208	19.5	139	-0.012	0.023	14.4
Congo, DR	ZAR	Sub-Saharan Africa	158	0.002	0.001	43.1	.	.	.	.	.	.	.	.
Cook Islands	COK	Oceania	1,363	0.003	0.113	78.4	.	.	.	.	.	.	.	.
Croatia	HRV	Central and Eastern Europe	10,831	-0.013	0.304	97.4	303	-0.036	0.061	42.9	1,345	-0.016	-0.003	48.8
Cuba	CUB	Caribbean	.	.	.	.	2,059	-0.138	0.060	31.5	224	-0.006	0.006	20.5
Cyprus	CYP	South Europe	4,411	0.004	0.191	97.4	88	0.007	0.029	0.0	.	.	.	.

Czech Republic	CZE	Central and Eastern Europe	1,674	-0.001	0.067	62.6	495	-0.015	0.125	17.5	1,099,078	-0.032	0.037	.
Denmark	DNK	Western Europe	615	-0.006	0.017	79.3	595	0.016	0.300	48.6	206	0.033	0.243	21.8
Dominican Rep.	DOM	Caribbean	.	.	.	.	5,736	-0.015	0.294	25.0	.	.	.	.
East Africa, other	EAf	Sub-Saharan Africa	211	-0.003	0.001	62.8	.	.	.	.	144	0.029	-0.002	12.5
East Europe, other	EEu	Central and Eastern Europe	696	-0.007	0.024	88.8	.	.	.	.	.	.	.	.
Ecuador	ECU	South America	692	-0.006	0.016	82.7	7,978	-0.12	0.460	24.2	.	.	.	.
Egypt	EGY	Middle East and North Africa	16,237	-0.049	0.295	79.0	.	.	.	.	293	-0.053	0.019	15.8
El Salvador	SLV	Central America	1,138	-0.002	0.084	96.7	.	.	.	.	.	.	.	.
England	ENG	Western Europe	129,138	-0.119	0.671	76.0	.	.	.	.	.	.	.	.
Eritrea	ERI	Sub-Saharan Africa	105	0.010	0.007	60.2	.	.	.	.	.	.	.	.
Estonia	EST	Central and Eastern Europe	192	-0.001	0.003	57.8	191	0.082	0.032	.	93	-0.005	0.024	16.1
Ethiopia	ETH	Sub-Saharan Africa	727	-0.005	0.056	60.0	.	.	.	.	.	.	.	.
Europe, other	Eur	Western Europe	.	.	.	.	9,128	-0.061	0.214	54.7	127	-0.010	0.010	28.3
Fiji	FJI	Oceania	29,161	-0.010	0.533	79.8	.	.	.	.	.	.	.	.
Finland	FIN	Western Europe	443	-0.008	-0.001	76.6	499	0.015	0.233	25.0	200	0.004	0.008	20.0
France	FRA	Western Europe	7,533	0.003	0.393	44.0	14,285	0.138	0.716	37.6	2,315	0.131	0.082	22.0
Gaza Strip	GAZ	Middle East and North Africa	857	-0.003	0.101	82.0	.	.	.	.	.	.	.	.
Georgia	GEO	Former Soviet Union	.	.	.	.	.	.	.	.	540	0.011	0.002	18.1
Germany	DEU	Western Europe	14,049	-0.084	0.133	78.4	6,808	-0.011	0.691	49.4	3,431	-0.007	0.009	35.4
Ghana	GHA	Sub-Saharan Africa	1,700	0.003	0.108	58.5	.	.	.	.	143	0.072	0.001	11.9
Greece	GRC	South Europe	25,058	0.025	0.618	94.9	1,034	0.023	0.262	19.9	404	-0.063	0.043	32.7
Guinea	GIN	Sub-Saharan Africa	115	0.007	0.025	27.8	.	.	.	.	.	.	.	.
Hong Kong	HKG	Eastern Asia	38,669	-0.042	0.585	82.1	.	.	.	.	.	.	.	.
Hungary	HUN	Central and Eastern Europe	3,220	0.005	0.081	84.2	783	0.079	0.215	8.2	1,453	-0.134	-0.013	9.3
Chile	CHL	South America	9,251	-0.020	0.207	87.1	3,778	-0.095	0.257	18.3	.	.	.	.
China	CHN	Eastern Asia	221,952	0.109	0.706	48.1	19,783	0.128	0.444	27.8	3,956	0.076	0.025	24.5
India	IND	South Asia	127,553	0.098	0.744	37.1	.	.	.	.	1,026	0.042	0.005	5.8
Indonesia	IDN	South-East Asia	27,611	-0.008	0.510	60.1	.	.	.	.	99	0.018	0.007	22.2
Iran	IRN	Middle East and North Africa	20,007	-0.024	0.252	48.5	.	.	.	.	214	0.055	-0.005	8.4
Iraq	IRQ	Middle East and North Africa	38,309	0.161	0.861	50.8	.	.	.	.	136	-0.019	0.002	26.5
Ireland	IRL	Western Europe	16,036	-0.036	0.443	57.0	1,061	-0.006	0.359	32.2	520	0.069	0.028	22.8
Israel	ISR	Middle East and North Africa	2,170	0.010	0.398	76.7	.	.	.	.	481	0.021	0.092	18.9
Italy	ITA	South Europe	37,411	-0.069	0.486	87.8	28,534	0.038	0.800	20.8	2,230	0.079	0.030	28.8
Japan	JPN	Eastern Asia	10,226	0.002	0.391	59.6	.	.	.	.	883	0.151	0.006	7.1
Jordan	JOR	Middle East and North Africa	2,489	0.001	0.130	68.4	.	.	.	.	93	0.001	-0.003	46.2
Kazakhstan	KAZ	Former Soviet Union	185	-0.001	0.019	47.7	.	.	.	.	3,234	0.032	0.000	6.9
Kenya	KEN	Sub-Saharan Africa	1,332	-0.003	0.021	61.7	.	.	.	.	.	.	.	.
Korea, South	KOR	Eastern Asia	47,645	0.077	0.563	56.8	.	.	.	.	793	0.129	0.057	3.2
Kosovo	KOS	Central and Eastern Europe	104	0.010	0.025	83.4	.	.	.	.	324	0.054	0.016	23.4

Kuwait	KWT	Middle East and North Africa	1,478	-0.004	0.066	58.2	.	.	.	.	.	.	.	.
Kyrgyzstan	KGZ	Former Soviet Union	.	.	.	.	.	.	.	.	378	0.009	0.004	4.7
Laos	LAO	South-East Asia	4,190	0.033	0.482	93.1	.	.	.	.	.	.	.	.
Latvia	LVA	Central and Eastern Europe	277	-0.005	0.000	84.0	286	0.095	0.093	0.0	193	-0.019	-0.004	12.9
Lebanon	LBN	Middle East and North Africa	53,988	0.073	0.757	87.6	.	.	.	.	118	-0.026	-0.003	47.5
Liberia	LBR	Sub-Saharan Africa	323	-0.005	0.045	53.0	.	.	.	.	.	.	.	.
Libya	LBY	Middle East and North Africa	124	0.006	0.000	59.6	.	.	.	.	80	0.029	-0.001	20.0
Lithuania	LTU	Central and Eastern Europe	377	-0.006	0.003	52.3	425	0.103	0.123	0.0	264	-0.024	-0.002	20.5
Luxembourg	LUX	Western Europe	.	.	.	.	32	-0.091	0.050	.	.	.	.	.
Macau	MAC	Eastern Asia	466	-0.008	0.009	80.7	.	.	.	.	.	.	.	.
Macedonia	MKD	Central and Eastern Europe	9,965	0.040	0.542	93.2	.	.	.	.	834	-0.064	0.029	16.3
Malaysia	MYS	South-East Asia	26,040	-0.094	0.359	69.8	.	.	.	.	109	0.059	0.047	0.0
Malta	MLT	South Europe	9,431	0.010	0.342	98.9	29	-0.142	0.066	100.0	.	.	.	.
Mauritius	MUS	Sub-Saharan Africa	3,753	-0.005	0.070	81.6	.	.	.	.	.	.	.	.
MENA, other	MENA	Middle East and North Africa	466	-0.006	0.062	64.7	.	.	.	.	218	0.021	-0.002	23.9
Mexico	MEX	Central America	921	-0.008	0.023	31.0	.	.	.	.	238	-0.052	0.014	5.5
Moldova	MDA	Former Soviet Union	.	.	.	.	.	.	.	.	1,522	-0.107	-0.003	8.5
Mongolia	MNG	Eastern Asia	1,429	0.017	0.243	6.6	.	.	.	.	759	0.047	0.009	9.6
Montenegro	MNE	Central and Eastern Europe	167	0.000	0.007	85.7	.	.	.	.	96	-0.008	-0.003	31.3
Morocco	MAR	Middle East and North Africa	239	-0.003	0.022	60.5	12,803	0.088	0.484	38.7	122	-0.052	0.017	39.3
Nepal	NPL	South Asia	29,878	0.128	0.645	9.1	.	.	.	.	84	0.055	0.003	3.6
Netherlands	NLD	Western Europe	5,618	-0.017	0.109	81.7	2,759	0.075	0.523	40.5	819	0.026	0.081	28.0
New Caledonia	NCL	Oceania	117	0.007	0.016	75.2	.	.	.	.	.	.	.	.
New Zealand	NZL	Oceania	78,627	-0.282	0.125	73.3	.	.	.	.	.	.	.	.
Nicaragua	NIC	Central America	233	-0.003	0.002	91.8	.	.	.	.	.	.	.	.
Nigeria	NGA	Sub-Saharan Africa	1,474	0.000	0.089	36.0	907	0.196	0.478	26.7	410	-0.042	0.031	16.1
Niue	NIU	Oceania	115	0.007	0.036	75.8	.	.	.	.	.	.	.	.
Northern Ireland	NIR	Western Europe	2,035	-0.005	0.022	78.1	.	.	.	.	.	.	.	.
Norway	NOR	Western Europe	311	-0.006	0.023	55.6	384	0.012	0.193	38.5	145	0.026	0.003	24.0
Oceania and Stateless	Oce	Oceania	.	.	.	.	512	-0.012	0.329	41.3	.	.	.	.
Oceania, other	Oce	Oceania	188	-0.001	-0.003	74.1	.	.	.	.	67	-0.021	0.014	23.9
Oman	OMN	Middle East and North Africa	158	0.001	0.072	35.0	.	.	.	.	.	.	.	.
Other	Oth	Other	271,275	-0.151	0.202	71.7	.	.	.	.	.	.	.	.
Pakistan	PAK	South Asia	21,809	0.037	0.609	36.8	19,196	0.205	0.691	24.3	292	0.064	0.002	23.6
Papua New Guinea	PNG	Oceania	1,539	0.000	0.089	91.9	.	.	.	.	.	.	.	.
Paraguay	PRY	South America	.	.	.	.	3,968	0.024	0.155	11.5	.	.	.	.
Peru	PER	South America	3,749	-0.006	0.033	69.4	8,316	-0.061	0.250	21.8	88	-0.023	-0.002	23.0
Philippines	PHL	South-East Asia	72,271	-0.046	0.592	66.4	.	.	.	.	318	0.082	-0.001	5.0
Poland	POL	Central and Eastern Europe	8,696	-0.041	0.012	83.5	2,611	0.049	0.238	33.5	2,821	-0.115	0.006	43.1

Portugal	PRT	South Europe	5,329	0.017	0.409	89.2	4,391	-0.083	0.324	26.0	203	-0.004	-0.002	11.3
Qatar	QAT	Middle East and North Africa	101	0.010	0.012	50.2	.	.	.	.	.	.	.	.
Romania	ROM	Central and Eastern Europe	1,820	-0.004	0.026	79.6	6,985	-0.107	0.152	9.1	2,455	-0.116	0.005	5.7
Russia	RUS	Former Soviet Union	5,348	-0.005	0.182	57.0	6,980	-0.099	0.273	21.4	21,115	0.069	0.039	10.8
Samoa	WSM	Oceania	7,212	0.024	0.418	66.6	.	.	.	.	.	.	.	.
Saudi Arabia	SAU	Middle East and North Africa	2,084	0.008	0.158	29.3	.	.	.	.	.	.	.	.
Scotland	SCO	Western Europe	12,903	-0.079	0.164	82.4	.	.	.	.	.	.	.	.
Senegal	SEN	Sub-Saharan Africa	.	.	.	.	1,293	0.179	0.295	26.4	.	.	.	.
Serbia	YUG	Central and Eastern Europe	4,619	0.007	0.242	91.1	.	.	.	.	1,720	-0.075	0.002	38.0
Serbia and Montenegro	YUG	Central and Eastern Europe	.	.	.	.	.	.	.	.	122	-0.052	0.008	38.0
Sierra Leone	SLE	Sub-Saharan Africa	1,190	0.000	0.128	43.0	.	.	.	.	.	.	.	.
Singapore	SGP	South-East Asia	9,131	-0.035	0.169	68.0	.	.	.	.	.	.	.	.
Slovakia	SVK	Central and Eastern Europe	1,159	-0.005	0.057	58.0	347	-0.032	0.078	25.0	26,913	-0.119	0.008	31.8
Slovenia	SVN	Central and Eastern Europe	551	-0.006	0.017	90.5	158	-0.098	0.109	0.0	220	0.003	-0.003	33.5
Solomon Islands	SLB	Oceania	136	0.004	0.040	84.5	.	.	.	.	.	.	.	.
Somalia	SOM	Sub-Saharan Africa	647	-0.003	0.139	66.8	.	.	.	.	.	.	.	.
South Africa	ZAF	Sub-Saharan Africa	31,731	-0.032	0.422	70.7	.	.	.	.	105	-0.023	0.032	26.4
South Africa, other	SAf	Sub-Saharan Africa	180	-0.001	0.004	67.4	.	.	.	.	135	-0.004	0.004	28.1
South America, other	SAm	South America	122	0.006	-0.002	81.5	.	.	.	.	210	-0.054	0.015	22.4
South and Central Asia, other	SCA	Former Soviet Union	342	-0.005	0.001	47.4	.	.	.	.	74	-0.020	0.006	20.3
South Eastern Europe, other	SEE	Central and Eastern Europe	4,547	0.001	0.190	98.1	.	.	.	.	.	.	.	.
South Sudan	SSD	Sub-Saharan Africa	660	-0.004	0.065	66.0	.	.	.	.	.	.	.	.
South-East Asia, nfd	SEA	South-East Asia	.	.	.	.	.	.	.	.	78	0.036	0.004	9.0
Spain	ESP	South Europe	3,064	-0.002	0.082	64.3	1,335,902	-0.024	0.759	97.8	701	-0.036	0.003	17.1
Sri Lanka	LKA	South Asia	25,022	0.030	0.594	63.7	.	.	.	.	.	.	.	.
Sudan	SDN	Middle East and North Africa	3,987	0.017	0.238	77.5	.	.	.	.	.	.	.	.
Sweden	SWE	Western Europe	1,215	-0.004	0.096	56.9	1,837	0.135	0.537	17.4	424	-0.013	0.121	30.7
Switzerland	CHE	Western Europe	1,241	-0.003	0.038	72.9	.	.	.	.	245	0.005	0.033	41.6
Syria	SYR	Middle East and North Africa	7,663	0.032	0.456	54.9	.	.	.	.	347	-0.014	-0.003	28.3
Taiwan	TWN	Eastern Asia	10,377	0.002	0.329	58.3	.	.	.	.	131	0.038	0.002	5.3
Tajikistan	TJK	Former Soviet Union	.	.	.	.	.	.	.	.	91	0.038	-0.006	3.3
Tanzania	TZA	Sub-Saharan Africa	216	-0.003	-0.004	73.7	.	.	.	.	.	.	.	.
Thailand	THA	South-East Asia	20,520	0.024	0.423	43.1	.	.	.	.	430	0.110	0.047	7.7
Timor-Leste	TMP	South-East Asia	1,465	0.007	0.107	97.7	.	.	.	.	.	.	.	.
Tokelau	TKL	Oceania	200	0.000	0.053	62.3	.	.	.	.	.	.	.	.
Tonga	TON	Oceania	4,119	0.004	0.159	79.1	.	.	.	.	.	.	.	.
Tunisia	TUN	Middle East and North Africa	.	.	.	.	.	.	.	.	317	-0.110	0.010	27.4
Turkey	TUR	Middle East and North Africa	10,131	0.012	0.489	84.8	.	.	.	.	724	-0.006	0.016	14.6
Uganda	UGA	Sub-Saharan Africa	283	-0.005	0.000	68.2	.	.	.	.	.	.	.	.

UK	GBR	Western Europe	658	-0.007	0.020	60.8	7,127	-0.051	0.741	34.8	3,214	0.071	0.068	20.4
Ukraine	UKR	Former Soviet Union	3,131	0.013	0.243	76.3	4,530	0.081	0.109	23.6	45,221	-0.028	0.007	12.5
United Arab Emirates	ARE	Middle East and North Africa	1,353	-0.007	0.020	43.4	.	.	.	.	.	.	.	.
Uruguay	URY	South America	3,671	0.005	0.056	96.6	1,461	-0.067	0.085	20.3	.	.	.	.
USA	USA	North America	19,011	-0.061	0.395	55.5	.	.	.	.	3,560	0.059	0.039	24.9
Uzbekistan	UZB	Former Soviet Union	230	-0.003	-0.001	50.3	.	.	.	.	1,251	0.018	0.003	2.7
Venezuela	VEN	South America	1,117	-0.003	0.028	33.7	6,252	-0.161	0.282	9.9	.	.	.	.
Vietnam	VNM	South-East Asia	79,276	0.139	0.812	76.9	.	.	.	.	11,516	0.114	0.133	38.0
Wales	WAL	Western Europe	1,973	-0.004	0.038	74.1	.	.	.	.	.	.	.	.
Zambia	ZMB	Sub-Saharan Africa	172	-0.001	0.009	75.1	.	.	.	.	.	.	.	.
Zimbabwe	ZWE	Sub-Saharan Africa	3,049	-0.003	0.052	58.1	.	.	.	.	.	.	.	.

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