Moving to Segregation: Evidence from 8 Italian cities *

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Abstract

We use a new dataset and a novel identification strategy to analyze the effects on labor market outcomes of residential segregation of migrants in 8 Italian cities. Our data are representative of the population of both legal and illegal migrants, allow us to measure segregation at the very local level (the block) and include measures of housing prices, commuting costs and migrants' linguistic ability. We find evidence that migrants who reside in areas with a high concentration of non-Italians are less likely to be employed compared to similar migrants who reside in less segregated areas. In our preferred specification, a 10 percentage points increase in residential segregation reduces the probability of being employed by 7 percentage points or about 8% over the average. Additionally, we also show that this effect emerges only above a critical threshold of 15-20% of migrants over the total local population, below which there is no statistically detectable effect. Contrary to common wisdom, in our data migrants seem to be positively selected into segregated areas. A simple matching model with heterogeneous workers and endogenous sorting into heterogeneous locations rationalizes our findings and is supported by additional empirical results.

JEL Codes: J15,J61,R23.
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1 Introduction

Residential segregation of migrants and minorities is a common feature of most cities in the developed world (Borjas, 1995; Card and Rothstein, 2007; Cutler and Glaeser, 1997; Cutler, Glaeser, and Vigdor, 1999; Ross, 1998) and its role in the process of economic and social integration is at the forefront of the political debate. In the US, this debate, at both a policy and academic level, is long standing and the literature, both theoretical and empirical, offers mixed results.

For example, Munshi (2003) studies Mexican migrants in the US and finds that a larger number of migrants in one's same US location improves employment and wage outcomes. On the other hand, Kling, Liebman, and Katz (2007) exploit a randomized experiment (Moving to Opportunity) that offered families that lived in poor neighborhoods the opportunity to move in better areas and show no significant effects on adult economic self-sufficiency (although program participants did take the opportunity to move).

In Europe, residential segregation is a relatively novel issue that is attracting increasing attention due to the political pressures associated to large immigration flows in most European countries (OECD, 2009). There is a paucity of data and the few studies available, as for the US, produce mixed results. Clark and Drinkwater (2000, 2002) document that in the UK the poor areas where ethnic minorities live are associated with higher unemployment rates and lower self-employment rates. On the other hand, using a natural experiment (i.e. a spatial dispersal policy under which refugees were randomly assigned to locations), Edin, Fredriksson, and Åslund (2003) and Damm (2009), for Sweden and Denmark, respectively, find strong evidence that the size of ethnic enclaves are positively correlated with earnings and job finding rates.

In this paper we contribute to this debate by producing empirical evidence using a new and unique survey conducted in 2009 in 8 cities located in the north of Italy. Our data allow us to improve on previous studies along four dimensions.

First, the survey covers both legal and illegal migrants, thanks to a particular sampling frame which randomly draws blocks from the continuum of map locations within cities (in Section 2 we describe the survey in details). We find that over 10% of migrants in our data are illegally resident in the country and they are far from being a random subgroup of the entire population so that excluding them from any analyses may lead to inaccurate inference.

Second, the data are available at a very detailed level of geographical disaggregation, namely we can identify the exact city block where each interviewed person resides. Hence, we can define residential segregation more accurately than in most previous studies, i.e. at the level of the individual block. Bayer, Ross, and Topa (2008), indeed, shows that this is the relevant definition. Additionally, our data include objective measures of the linguistic abilities of migrants, as a formal test of the knowledge of the Italian language was carried out at the end of most personal interviews (87%).

Third, by merging our survey with data from the national census, we are able to measure various physical characteristics of the buildings in each block, which are valid instruments for residential segregation, once conditioning on local house prices, as detailed in Section 3. We also rely on mobility costs, notably measures of travel times to central urban areas using public transportation, as additional controls. Contrary to Bayer et al. (2008), whose identification rests on neighborhood fixed-effects, our instrumental variable approach is robust to the presence of unobservable factors at any level of geographical disaggregation (including the block).

Fourth, we allow for discontinuities in the relationship between residential segregation and labor market outcomes. This enables us to identify a critical threshold value above which residential segregation is harmful to employment of migrants. This result is important to assess the scope for relocation policies in cities having experienced a recent large immigration wave.

Italy is a particularly interesting case to study, as the Italian population of migrants increased by a factor of 5 between 1990 and 2010. In the OECD area only Spain attracted a larger number of migrants relative to the native population over the same time period. At the same time, migrants appear to be highly segregated in terms of their residential locations. Based on official data from the 2001 census, the coefficient of variation of the number of resident migrants across census tracts is twice as large as that of natives (1.793 against 0.966 for natives). Being migration a recent phenomenon, we are dealing mostly with first generation migrants.

This supports our choice to consider employment as the key economic outcome in our aalysis.

The focus on a limited group of 8 cities in Northern Italy allowed us to design the sampling frame very carefully and to use a comprehensive questionnaire for the interviews, thus providing a valuable data set to analyze what lies behind the observed effects of residential segregation on job finding.

Our main results show that migrants who reside in areas with a high concentration of non-Italians are less likely to be employed compared to similar migrants who reside in less segregated areas. The magnitude of these effects is non negligible: in our preferred specification a 10 percentage points increase in residential segregation reduces the probability of being employed by 7 percentage points or about 8% over the average. Additionally, we also show that this effect varies discontinuously around a key threshold value of 15-20% of migrants over the total local population. Below the threshold there is no statistically detectable effect, while a negative and significant impact of residential segregation emerges above the threshold.

Interestingly, our instrumental variable estimates are more negative than those that do not control for endogenous sorting, suggesting that, contrary to the common wisdom, there might be positive selection of migrants into segregated city neighborhoods.

We then provide an interpretation of the results using a matching model with endogenous sorting and double heterogeneity. Workers with different productivities face a trade-off in their location decisions across two locations, one that is characterized by high housing and low job destruction and one where rents are low but jobs are destroyed more frequently. For simplicity, the model assumes that natives are immobile and labor markets are segmented - i.e. one can only find jobs in the area where one resides -, although these assumptions can easily be relaxed without changing our main theoretical findings. In partial equilibrium, the model delivers the common negative sorting result, with migrants of lower quality endogenously deciding to reside in the low rent-bad jobs areas. In general equilibrium, however, labor demand also adjusts endogenously to changes in the average productivity of workers in each area, as employers optimally choose their locations. In a general equilibrium setting the disincentive for the high productivity workers to move to the low rent areas is mitigated by the feedback effect that such a move would induce on labor demand, which would react to the increase in average productivity in the location by creating more jobs. Under these circumstances, if enough highly productive workers are willing to move into the low rent areas, then an equilibrium with positive sorting might arise.

Although matching models with double heterogeneity (in both jobs and workers) have been already developed (Albrecht and Vroman, 2002), the application of such a theoretical framework to the issue of residential segregation is entirely novel. In the context of our analysis, the model provides a coherent interpretation for the two key empirical findings of Section 4, namely the negative effect of segregation on labor market outcomes and the apparent positive selection of migrants in segregated areas. The first of such results is due to the lower job destruction rate in the high rent areas while positive selection is a feature of some general equilibria. Notice that, our theory does not necessarily contradicts the common belief that in segregated areas hiring networks may work efficiently in helping workers find employment (Munshi, 2003), as high job finding rates may well coexist with high job destruction rates.

The implications of the model are confirmed by a set of additional empirical findings that we present in Section 5.7. Specifically, we find that the simple non-IV estimates are positive in the subsample of the high skilled and negative for the low skilled, while the IV results are broadly comparable, consistently with positive selection of migrants into segregated neighborhoods.

The plan of the paper is as follows. Section 2 describes the data, section 3 outlines the identification strategy, Section 4 presents our empirical results. In Section 5 we develop a simple theory that provides a useful framework for the interpretation of our empirical results. Finally, Section 6 briefly characterizes the normative implications of our results and concludes.

2 Data and descriptive evidence

Our analysis is based on data from a new survey of immigrants, which was carried out between October and November 2009 in eight cities in Northern Italy: Alessandria, Brescia, Bologna, Lucca, Milano, Prato, Rimini and Verona. The cities were chosen non-randomly to represent agglomerations of different sizes (large, medium-sized and small) while at the same time guaranteeing a good degree of representativeness of the entire population of the North of Italy, where more than 60 per cent of the migrant population is located.

[insert Figure 1 here]

Figure 1 shows the locations of the 8 surveyed cities on the map of Northern (and Central) Italy while Table 1 reports some key characteristics of these cities and compares them with the averages in the country. Milan is the largest city in the sample, and also one of the largest in Italy (together with Rome and Naples), Bologna, Brescia and Verona are middle-sized, while Alessandria, Lucca, Prato and Rimini can be classified as small cities. In terms of income per capita, the 8 surveyed cities are more homogeneous, with the exception of Milan, whose 21,000 euros of annual gross income per capita place it among the richest city in the country. Average age is generally higher than the country average, with Bologna having the oldest population and Prato the youngest. Given the large regional differences in labor market performance, both the unemployment and the employment rates of the 8 surveyed cities are, respectively, lower and higher than the country average and around the average of the Northern regions. Overall, the figures in Table 1 suggest that our sample offers a good representation of the population of the North of Italy.

[insert Table 1 here]

In Table 2 we also show the incidence of migrants in each of the surveyed cities. In columns 1 and 2 we report the official shares of the non-Italian residents in the entire city and in the surveyed neighborhoods only. These figures are computed from the local population registers, hence, they can only capture legal migrants. The comparison of the two columns suggests that the extent of oversampling in our survey is substantial but not enormous. Additionally, these data also show that the 8 surveyed cities are characterized by high levels of migration, well above the country average (around 6%) or the average in the northern regions (7%).

The particular sampling frame of our survey (see Section 2.1 below) guarantees that both legal and illegal migrants are covered. In columns 3, 4 and 5 of Table 2 we show the distribution of migrants by legal status on the basis of our preferred definition. Under such a definition we code as illegal migrants all citizens of a non-EU country who declare that they do not have a permit of stay or refuse to answer the question on legal status and all citizens of a EU country who are not employed and declare that they do not have a permit of stay or refuse to answer. This definition is motivated by the fact that for several EU countries of recent access (e.g. Bulgaria and Romania) there are still restrictions to freedom of movement and/or work. As it is evident from the figures, the ability to cover also illegal migration is a major advantage of our data. In all cities, undocumented migrants represent a sizable proportion of total migration: from 8% in Rimini to over 22% in Brescia.[1] This feature of our data allows us to measure the concentration of non-Italians living nearby more precisely than in previous studies. In our empirical analysis we use the information about legal status as a control. Our findings (Section 4) reveal that being an illegal immigrant is an important predictor of employment probability. Although our main results remain qualitatively unchanged if we exclude this portion of migrants, the magnitude of the estimated impact of residential segregation on employment prospects varies noticeably (see Table 12).

[insert Table 2 here]

2.1 The sampling procedure

The sampling procedure of our survey was designed with the intent to reach particularly hard-to-trace segments of the population, namely immigrants and, particularly, illegal immigrants. Migrants are grouped into three macro regions of origin and the survey guarantees representative results only within these three subpopulations: European new member states (NMS)[2], Western Balkan countries (WBS) [3] and all other countries of origin.[4]

[1]If we classify as legal immigrants all those who are citizens of EU countries, the percentage of illegal migrants almost halves.

[2]Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovak Republic and Slovenia.

[3]Albania, Bosnia, Croatia, Macedonia, Kosovo, Montenegro and Serbia.

[4]The focus on European new member states and the Western Balkan countries was imposed by the European Bank for reconstruction and Development (EBRD), the sponsor of the study.

The sampling strategy consists of three main steps: in the first stage we sample neighborhoods in each of the 8 cities and then, in the second step, we select one block of buildings in each of the sampled neighborhoods where, in the final step, the individuals to be interviewed are chosen.

The selection of the neighborhoods is based on a mere geographical criterion and it is aimed at identifying those areas where the probability of finding foreign residents is higher. The neighborhoods are, therefore, selected with sampling probabilities that are proportional to the share of legal migrants resident in the neighborhood, as measured by the official population registers. Subsequently, one block of buildings is chosen in each neighborhood, by picking random points from the official city maps released by the city councils[5]. The selection of the blocks is performed on the basis of a simple algorithm that randomly selects points on the maps and then picks the closest block, where blocks are defined as portions of urban surface that are built-up and continuous, i.e. not interrupted by areas for traffic circulation or allocated for public use (e.g. parks).[6]

In each selected block a census of residential units is carried out, so that we know the total number of households in each block as well as their origin. This census is based on a combination of conversations with the buildings' janitors and short door-to-door visits. Within each block 4 persons are randomly selected for each of the population groups that we consider (NMS, WBS, other non-Italians and Italians), so that a maximum of 16 persons are eventually interviewed. Obviously, in most blocks there are fewer that 16 interviews because there were fewer than 4 persons in some of the population groups.[7] This particular process of selection is meant to guarantee a sufficient number of cases to allow meaningful analyses by population groups.

[5]The website http://v.controul.com/app/ shows exactly which blocks were chosen in each neighborhood.

[6]In order to increase sample size, while at the same time maintaining the distribution of population groups (natives and immigrants) additional blocks are selected based on a proximity criterion. Namely, we also include in the survey blocks that are adjacent to one (or more) of the randomly selected blocks where the share of dwellings occupied by immigrant households is higher than a fixed threshold. Since the randomly selected blocks that satisfy the threshold criterion are usually adjacent to several other blocks, only the one adjacent block with the highest incidence of immigrants is selected.

[7]Only individuals older than 18 are eligible for the interview and no more than one person per household is selected.

[insert Table 3 here]

Table 3 summarizes the sampling procedure. Each city is divided in 3 districts: central, mid-central and peripheral. The first three columns of the table indicate the number of sampled blocks in each city and district. The fourth columns simply sums over the first three and reports the total number of sampled blocks. The average number of interviews/observations per block is shown in column 5. In columns 4 and 5 we also show in parentheses the total number of blocks in the city (column 4) and the average population in the blocks, so as to give an indication of the coverage of our sample.

The census of the residential units in each block is a particularly precious source of information. Official population registers from the city councils only consider regular immigrants while our census includes both legal and illegal immigrants, living, either permanently and temporarily, in the considered blocks. We use the block census to construct our measure of residential segregation.

Although the survey includes both migrants and natives, for this study we only consider the subsample of migrants. Interviewees are asked questions on individual and family characteristics, reasons behind migration, living and work conditions, cultural integration and compliance with immigration laws.[8] Additionally, every interviewed person is asked to take an optional language test consisting in a series of questions of growing complexity.[9]

2.2 Descriptive statistics

Given the peculiar sampling structure of our study, we start by comparing our data with other surveys that might be used to conduct studies of migration, namely the official Labour Force Surveys (LFS) and a survey of migrants carried out by the institute *Iniziative e Studi sulla*

[8]Especially for the questions about legal status, the interviewers were very carefully instructed to insist on the fact that the survey was carried out exclusively for research purposes, that the data would remain fully anonymous and that none of the institutions involved in the organization of the survey was in any way connected with the immigration authorities, the police or the ministry of internal affairs (which is the institution that releases work and residence permits).

[9]To encourage the taking of the test a small amount of 5 euros was offered.

Multietnicità (ISMU), which is relatively popular in Italy (Dustmann, Fasani, and Speciale, 2010).

[insert Table 4 here]

While the LFS data only capture legal migrants, being sampled from the population registers, the ISMU survey also includes illegal migrants but its sampling frame is radically different from ours (Cesareo and Blangiardo, 2009).[10] In particular, the ISMU survey was carried out between October 2008 and February 2009 in 32 cities all over Italy. Immigrants are interviewed in places where they usually meet or go to seek assistance, such as language schools, immigrant assistance centers, trade unions. The advantage of this sampling method is that it makes it much easier to reach illegal immigrants, thus allowing for larger sample sizes.[11] However, such an advantage comes at the cost of representativeness, as migrants who are likely to be found in the places visited by ISMU might be very different from the rest.

By construction, migrants are over-represented in our data compared to the LFS, both overall and for each of the subgroups that we consider (NMS, WBS and others), which are equally represented (also by construction).[12] Also, we find slightly more illegal migrants compared to ISMU, although the difference is minor. Female migrants are under-represented in our data compared to both the LFS and ISMU, while the education distribution is remarkably similar. Our interviewees are also more likely to be in employment, a result that is due for the most part to the presence of illegal residents, who are very frequently employed in the shadow sector.

We now focus exclusively on our data and Table 5 provides a description of the main variables used in our empirical exercise of Section 4.

[insert Table 5 here]

On average, migrants are quite younger than natives, with an average age of about 37 years old which compares to about 43 for Italians. Moreover, the incidence of females is much lower

[10] Unfortunately, the official Labour Force Survey is not representative at the level of the single municipality and the data for Table 4 are restricted to the North of Italy.

[11] The ISMU survey consists of 12,000 interviews to both regular and irregular immigrants.

[12] The ISMU survey covers only immigrants.

than among natives (46% against 52%). Immigrants into Italy do not appear to be a particularly low-skilled group; more than half of them have secondary education or above qualification. More than 10 percent of our surveyed immigrants are illegal. As already mentioned, the language test was optional and approximately 13% of the individuals in the sample refused to take it. The questionnaire also includes several questions on ownership of durables, which can be used as proxies of wealth: half of the sample own at least one car, 60% has internet connection at home and almost everybody has a cellular phone. In terms of labor market performance, roughly 90 percent are employed, which compares to a much lower employment rate for natives (about 50% in Northern Italy. See Table 1). Almost 60 percent obtained their jobs through friends and a third of the interviewees regularly work on Sundays. Throughout the analysis we make use of two alternative measures of segregation: the share of foreign households living in the considered blocks and the share of households belonging to similar ethnic groups (NMS, Western Balkans or other countries). The means and standard deviations of these indicators are reported in the last two rows of Table 5. On average there are over 16% of non-Italian households in the surveyed blocks, with a standard deviations of more than 10. When we look at segregation by macro region of origin, the percentage of households from one's same area in the block is just below 6%, with a standard deviation of 6.

In order to get a first glance at the pattern of residential segregation in our data, Table 6 reports the descriptive statistics on selected variables, distinguishing between immigrants living in high- and low-segregated areas, respectively defined as blocks where our preferred measure of residential segregation (share of non-Italians) lies in the top and bottom 25% of the observed distribution.[13] Interestingly, we do not find strong evidence indicating that more educated immigrants sort into less segregated areas. Also differences in car ownership, that can be taken as a proxy for wealth, are minimal. Immigrants residing in highly segregated neighborhoods are slightly older, they arrived in Italy more recently, they seem to be more likely to be employed, to work on Sundays and to have obtained a job through friends, although

[13] According to the distribution of immigrants in the considered blocks, the threshold level for the high-segregated neighborhoods (top 25% of the distribution) is 25.5% of foreign households and that for low-segregated (bottom 25%) is 7.5% of foreign households.

the row mean differences are not always statistically significant. Also, there does not seem to be a significant difference in the outcome of the language test between those living in high- and low-segregated blocks, although the share of those refusing the test varies significantly.

[insert Table 6 here]

In Figure 2 we also report standard dissimilarity indices computed for each of our 8 cities across census tracts using official data from the 2001 census (thus, excluding illegal migrants). The dissimilarity index measures the percentage of population that should be moved in order to reach a perfectly uniform distribution of migrants and natives across census tracts.[14] Bologna and Milan seem to be the cities with the most homogeneous distributions of migrants and natives across census tracts and, even in these cities, the dissimilarity index is quite high and indicates that more than one third of the population would have to be reshuffled in order to obtain a perfectly uniform distribution. In the most segregated cities, which are Alessandria and Brescia, this number peaks around 50%.

[insert Figure 2 here]

3 Empirical model and estimation startegy

Our empirical analysis is primarily aimed at estimating the causal effect of residential segregation on the labor market success of migrants. Our empirical model is based on the following main equation:

$$y_{icdb} = \alpha_1 RS_{cdb} + \alpha_2 X_i + \alpha_3 B_{cdb} + \delta_d + \delta_c + \epsilon_{icdb} \quad (1)$$

where y_{icdb} is a measure of labor market performance (employment) for migrant i in city c residing in district d and block b; RS_{cdb} is an indicator of residential segregation; X_i and B_{cdb}

[14]Let T_c be the total number of census tracts in city c, m_{tc} and n_{tc} the number of migrants and natives, respectively, residing in census tract t of city c, M_c and N_c the total number of migrants and natives, respectively, residing in city c, then the dissimilarity index for city c is computed as:

$$D_c = \frac{1}{2} \sum_{t=1}^{T_c} \left| \frac{m_{tc}}{M_c} - \frac{n_{tc}}{N_c} \right|$$

are sets of observable individual and block characteristics, respectively; δ_d is a district fixed effect; δ_c is a city fixed effect and ϵ_{icdb} is the error term. As mentioned above, in our empirical analysis we use two alternative measures of residential segregation, namely the percentage of either all non-Italians or migrants from i's same area of origin (NMS, Western Balkans and other countries) residing in block b of district d and city c.

The parameter of major interest in equation 1 is α_1. Its identification, however, is complicated by the presence of unobservable factors that influence both the location decisions of migrants and their labor market outcomes. For example, one might be worried that residentially segregated migrants are negatively selected, as only the very high ability can afford to live in native-dominated neighborhoods and high ability workers also experience better labor market outcomes, regardless of where they live. Such a mechanism would lead to underestimate α in standard OLS. Additionally, there might also be unobservable factors at the block level that influence both the migrant's probability of locating in the block as well as labor market success, such as the availability of public services (employment services, public transport).

More formally, one can think of the error term ϵ_{icdb} as being composed of three parts:

$$\epsilon_{icdb} = \eta_i + \Lambda_{cdb} + u_{icdb} \tag{2}$$

where η_i is an unobservable individual term, Λ_{cdb} is an unobservable block characteristic and u_{icdb} is a random term.[15]

The model is completed by an equation that defines residential segregation RS_{cdb}, which is the outcome of the joint process of residential location of both natives and migrants. We model RS_{cdb} in a reduced form framework as follows:

$$RS_{cdb} = \beta_1 B_{cdb} + \beta_2 C_{cdb} + \beta_3 \overline{X}_{cdb} + \Lambda_{cdb} + \overline{\eta}_{cdb} + v_{cdb} \tag{3}$$

where we distinguish two types of observable block characteristics: B_{cdb}, which are not ex-

[15]For simplicity we consider both η_i and Λ_{cdb} as scalars. The structure of our identification would be unchanged also in the presence of multiple unobservable components at either the individual or the block level.

cluded from equation 1, and C_{cdb}, which are excluded from equation 1. $\overline{X}_{cdb}$ is the vector of the average X_i among migrants in block cdb and, similarly, $\overline{\eta}_{cdb}$ is the average η_i among migrants in block cdb. v_{cdb} is a random term.

The presence of $\overline{\eta}_{cdb}$ and Λ_{cdb} on the right hand side of equation 3 generates endogeneity of RS_{cdb} in equation 1. In words, there might be unobservable characteristics of either the block (Λ_{cdb}) or the individuals (η_i) that affect both the location decisions and labor market outcomes. This is, in fact, the key identification issue in this literature and, as far as we know, it has never been addresses in a fully convincing way. Several studies eliminate the problem of correlation in unobservables at the neighborhood level (sorting) by using metropolitan-area level variables and exploiting cross-metropolitan variations (Card and Rothstein, 2007; Cutler and Glaeser, 1997; Evans, Oates, and Shwab, 1992; Ross, 1998; Ross and Zenou, 2008; Weinberg, 2000, 2004). Others are based on special social experiments or quasi-experimental data (see Bayer et al. (2008) for an extensive survey and a balanced view of the existing literature).

Perhaps the most convincing study so far is Bayer et al. (2008) who use data from the US Census, disaggregated at the level of the city block and city blocks are grouped into small sets of adjacent areas. Hence, they condition on block group fixed effects in their regression analysis to isolate block-level variation in neighbor attributes. Their identifying (untestable) assumption is the absence of correlation in unobservables across blocks within block groups. The particular sampling structure of our data does not allow us to adopt a similar strategy, as in each neighborhood only one block is sampled.

Our main identification strategy is different and it rests on the presence of excluded block characteristics C_{cdb}, i.e. the variables that, conditional on the set of controls, affect residential segregation and have no impact on the migrants' labor market outcomes. Such variables can be used to instrument RS_{cdb} in equation 1 for identifying the parameter α_1. This strategy improves upon Bayer et al. (2008), as it also controls for unobservable block characteristics.

More specifically, we use the physical characteristics of the buildings in the block 10 years before the survey as instruments for current residential segregation. Using the actual addresses of the residential units of the individuals in our sample, we have linked our data to an ancillary database of the 2001 Italian population census. Such an ancillary database contains a large set of descriptive characteristics of each single city block in Italy, including the number of buildings by decade of construction, the total amount of square meters in the block (i.e. the sum of the square meters of each floor in each building), broken down by residential and commercial space. We use these data to construct two instruments: the average age of the buildings in the block and the ratio of residential square meters per residential building in the block. The first variable obviously measures whether the block is composed of relatively new or old houses while the second takes high values in areas that are dominated by large residential buildings (lots of residential square meters for few buildings) and low values in areas with many smaller houses (e.g. residential villas, detached or semi-detached houses).

The validity of these instruments rests on the idea that the historical characteristics of the buildings are correlated with house prices and that migrants originally locate in areas with particularly convenient market conditions. Then, conditional on current housing prices, migrants have easier access to houses in areas where other migrants already reside. Importantly, our identification rests on a conditional exogeneity assumption, where the ability to observe and condition on current house prices as well as on other neighborhood characteristics is crucial. In particular, we also include in the set of controls an important indicator of neighborhood facilities, i.e. time to travel to the city center (by public transport).[16]

In order to document the relevance of our instruments, Table 7 reports the correlation coefficients computed on the sample of blocks in each city between the key variables that we will use in our analysis, namely the age of the buildings, housing density and the percentage of non-Italians in the block. Apart from Lucca, areas with the oldest buildings are also those with the lowest housing density, although the size of the correlation coefficient varies substantially from -0.9 in Rimini to -0.27 in Brescia (0.33 in Lucca). Interestingly, the correlation

[16]Our identification strategy is similar in spirit to the one that relies on the use of lagged values of the immigration-related variable in the different areas to instrument its current values (Altonji and Card, 1991). The use of historical area characteristics rather than the historical residential segregation rules out problems arising from the possible presence of area-level unobservable factors that are highly persistent over time and that are correlated with the settlement process and with the current labor market performance of migrants, e.g. see Pischke and Velling (1997)). We will use those more traditional instruments for robustness checks in Section 4.1.

between residential segregation and the physical characteristics of the buildings is very city-specific: when looking at building's age such a correlation is normally positive but in Bologna and Prato. Moreover, the correlation coefficients vary between -0.25 in Bologna to 0.515 in Brescia. Results for housing density are also heterogeneous across cities, as the correlation of this characteristic with residential segregation is negative in all cities but Bologna and Lucca and the range of variation remains very wide, from -0.33 in Alessandria and Verona to 0.21 in Lucca.

[insert Table 7 here]

The results in Table 7 justify the specification of our first stage regression (see Table A-1 in Section 4), where we interact both our instruments with city dummies to take into account the heterogeneity described in this table. The local patterns of spatial associations at the city-level are depicted in Figure A-1 in the Appendix. We construct quintile maps that depict the geographical distribution of residential segregation and our indicators of urban structure for the cities under analysis. Darker areas correspond to higher values of the inspected variable. For example, in Alessandria there is an important settlement of migrants in the northern outskirts of the city, where housing density is low and buildings are old; in Bologna we observe instead a substantial presence of immigrants in areas where buildings are more recently constructed (especially in the South-East); whereas in Brescia migrants are mainly located in the city center, where buildings are older and housing density is lower. Urban structure thus appears to be related to immigrant population density, with pronounced city-specific qualifications.

One potential concern with our identification strategy is related to the possibility that the physical characteristics of the residential buildings might reflect some unobservable individual characteristics, such as ability to live in better dwellings, that could also be correlated with one's employment outcomes. Although we believe that this is very unlikely, given that we control for a vast set of individual and area-level characteristics, including proxies for income, house prices and commuting times, in Table 8 we investigate the correlation between the most important individual observable characteristics in our data and the housing types where people reside, within cities and districts.

Specifically, we define dummy indicators for blocks where the average age of the buildings is above the mean (within cities) and where the density of houses is above the mean (within cities) and we run simple OLS regressions of individual observables (age, education and car ownership, years since migration) on such indicators, controlling for city and, in some specifications (odd columns) also district fixed effects. We find that none of the observables that we consider is significantly correlated with buildings' characteristics. Of course, our identification rests on the lack of such correlation among unobservable individual traits but finding a zero correlation for several different observable characteristics is already quite reassuring. Notice, additionally, that our instruments are measured in 2001 while the individuals in our sample are interviewed almost 10 years later, in 2009-2010. This should further reassure about the validity of our exclusion restrictions.

[insert Table 8 here]

Finally, notice that the outcome that we consider in our empirical application is a simple dummy indicator for employment, hence, we adopt a probit model. Nevertheless, we prefer to frame the discussion of the identification structure in a linear setting, as done in this section, in order to shows more clearly that we do not exploit the non-linearity of the probit model for identification purposes.

4 Empirical results

Table 9 reports the probit estimation results of model 1 where the dependent variable is the probability of being employed, using our alternative measures of segregation (columns 1 and 2, respectively), namely the share of foreign households in the block or the share of households from one's same group of origin. Columns 3 and 4 show the corresponding results where the segregation measures have been instrumented using the exogenous physical characteristics of the residential buildings interacted with city dummies. Table A-1 shows the first-stage results. Although the relationship between urban housing structure and residential segregation is different across cities (see Section 3), the instruments strongly predict immigrants residential patterns everywhere. The F-test of the excluded instruments range from around 300 to over 9,000, depending on the specification.

[insert Table 9 here]

Results show a negative and statistically significant impact of segregation on employment prospects, which is even more negative when using our instruments. When using the share of all foreign households in the block as a measure of segregation, the non-instrumented coefficient equals -0.012 and it is significant at the margin of the 10% level (column 1). The corresponding instrumented estimate is -0.055 and precision increases to the 5% level (column 3).[17] These coefficients correspond to marginal effects of the order of 1 to 7 percentage points increases in the probability of being employed for the average person in the sample. Our preferred specification, i.e. the instrumented estimates of column 3, suggests that a 10 percentage points increase in residential segregation reduces the probability of being employed by 7 percentage points or about 8% over the average.

The difference between the instrumented and the non-instrumented estimates is even more pronounced when we use the share of households from one's same group of origin as a measure of segregation (columns 2 and 4). In this case, the non-instrumented coefficient is indistinguishable from zero and it becomes a -0.054 with our IV strategy.

Although, the intrinsic non-linearity of the probit model generates marginal effects that vary over the distribution of the observables, the model estimated in Table 9 imposes that the sign of the relationship between the employment probability and the percentage of migrants in the block is fixed. However, the concept of residential segregation is related to the idea that migrants concentrate in certain areas and it is only when such a concentration is particularly high that it may become relevant for a variety of outcomes, like employment.

[17] The estimates are produced with conditional maximum likelihood and the standard errors are clustered at the city level.

The presence of variation in the percentage of migrants across blocks is a necessary condition for identification in our model of equation 1 but it is interesting to explore more in details if there are explicit (i.e. not mechanically due to the specific distributional assumptions) non-linearities in our data. In Table 10 we investigate the functional form of the relationship between residential segregation and employment. For brevity, we concentrate exclusively on the measure of segregation that yields the most significant results in our previous analysis of Table 9, i.e. the percentage of non-Italians in the block.

[insert Table 10 here]

In column 1 of Table 10, Panel A we simply add a quadratic term to the simple probit specification of Table 9, column 1. Figure 3 plots the marginal effect derived from these estimates over the distribution of our measure of segregation, together with 90% confidence intervals.[18] The marginal effect is computed at the sample average of all the other explanatory variables in the model. Results show a very interesting pattern, with the incidence of migrants in one's block being essentially uninfluential on employment until it reaches the threshold of 20%. After that threshold, which is located approximately around the 70% percentile of the distribution, the estimated marginal effect becomes negative and statistically significant at the 95% level and it remains rather constant for the remaining observable range of variation in residential segregation.

[insert Figure 3 here]

The results in Figure 3 are confirmed by the estimates reported in the other columns of Table 10, Panel A, where we replace the continuous indicator of the percentage of non-Italians in the block with dummies for blocks where such a percentage is above 5% (corresponding to the

[18]The marginal effect is computed as:

$$\frac{\partial Pr(y_{icdb} = 1 \mid X_{icdb})}{\partial RS_{cdb}} = \varphi(X_{icdb})(\alpha_{1,1} + \alpha_{1,2} RS_{cdb})$$

where X_{icdb} is the full set of explanatory variables of equation 1 and $\alpha_{1,1}$ and $\alpha_{1,2}$ are the coefficients on the linear and the quadratic terms of RS_{cdb}, respectively.

17th percentile), 10% (30th percentile), 15% (47th percentile), 20% (69th percentile) or 25% (75th percentile). The estimated coefficients on such dummies are positive and insignificant until the 15% threshold, when the effect becomes negative and significant. At higher levels of segregation (20% or 25%) we still find a negative effect but we loose statistical significance.

In Panel B of Table 10 we repeat this exercise instrumenting each of the dummies in columns 2 to 5 with our standard set of instruments, i.e. housing age and housing density interacted with city dummies. Since convergence of maximum likelihood probit models with multiple endogenous regressors is very hard to achieve, we do not replicate the results in column 1 of Panel A with instruments. Now the estimated coefficients are consistently negative throughout the distribution but show the same decreasing patters as in Panel A until the 20% threshold, when we also obtain statistical significance. Blocks with more than 25% of immigrants the effect is still negative, although slightly small in magnitude and less significant.

Overall, the results in Table 10 (and Figure 3) suggest that residential segregation generates a negative externality on the employment prospects of immigrants only when it reaches a threshold of approximately 15-20%. This is an important result that, from the policy perspective, opens the door to relocation policies that may increase the average level of employment.

Interestingly, we also find that residential segregation does not matter for the employment of natives (see Table A-2 in the Appendix), a result that is consistent with many papers (Angrist and Kugler, 2003; Bodvarsson, den Berg, and Lewer, 2008; Card, 1990, 2005; Friedberg and Hunt, 1995; Ottaviano and Peri, 2011).

The adverse effects of residential segregation that we find, especially in the IV specifications, are very hard to rationalize and, to our understanding, none of the models that have been proposed in this area of the literature provides a credible justification for it. In fact, if one believes the assumptions of our IV approach, the estimates of Table 9 and Table 10 should be purged of any effect due to unobservable factors both at the individual and at any local level, including the block. For example, they cannot be explained by the endogenous selection of people into residential areas as such a selection should be driven by individual unobservable factors. Moreover, the comparison of the IV and the un-instrumented results would suggest that a positive selection of immigrants into segregated areas, i.e. more employable workers reside in more segregated areas.

Similarly, models that rely on the popular spatial mismatch hypothesis (Kain, 1968; Ross, 1998; Weinberg, 2000, 2004) are also unable to explain our results, In fact, the traditional explanation of the negative effects of ethnic segregation on economic outcomes has primarily resorted to the spatial mismatch hypothesis as in Kain (1968). In its strict formulation, this theory predicts that adverse labor market outcomes of blacks in the US occur because they are located far away from jobs, in areas scarcely connected with the public transportation network and they, thus, find it difficult to access information about jobs and experience high time costs for traveling to work. If such an hypothesis holds true also in our Italian context and/or if workers were perfectly mobile across locations, our regression analysis, that controls for a measure of public transport availability and car access, should show no effect of ethnic segregation on employment outcomes. Additionally, our IV strategy should control for other local unobservable factors that may impede identification.

Another popular argument related to residential segregation is based on informal hiring networks in ethnic communities and it is supported by a growing US literature (Elliott, 2001; Falcon and Melendez, 1996; Mouw, 2002; Munshi, 2003). Moreover, Conley and Topa (2002) show that these network effects are found to be highly localized, even at the level of the housing block, as in Bayer et al. (2008). In fact, as we report in Table A-3, informal hiring networks seem to be present in our setting as those living in the most segregated areas are also more likely to find jobs through friends. However, the presence of local informal hiring networks should lead to a positive effect of segregation on employment probabilities, at least within some range.

To summarize, there are two key findings in this section that call for an explanation: first, the negative effect of residential segregation on the employment probability of migrants; second, the fact that the IV estimates are more negative than the corresponding un-instrumented estimates. In Section 5 we provide a simple model that is capable of rationalizing both result.

4.1 Robustness checks

In this section we perform two important checks of the robustness of our main results, namely those in Table 9.

[insert Table 11 here]

First, in Table 11 we replicate the estimates in Table 9 using alternative sets of instruments. In column 1 we only use housing density (interacted with the city dummies) and we exclude housing age from the set of instruments and we obtain an estimated effect that is still negative and significant, although a bit larger than our benchmark (Table 9, column 3).

In column 2 we do the opposite and use only housing age, excluding density. Now the estimated effect is still negative, smaller than the benchmark and it does not reach statistical significant at conventional levels.

In column 3 we substitute our measure of housing age in the block, which is computed on the basis of data collected during the 2001 census, with the same measure based on the previous census (1991). This is an important check given the rationale that we claim underlies the relevance of our instrument, namely the correlation between historical migration patterns and historical physical characteristics of the buildings. According to this argument, the farther back we can go in time to compute the instruments the better in terms of validity of the exogeneity assumption. Unfortunately, the 1991 census does not include measures of housing density, which appears to be the key excluded instrument in generating statistically significant effects, as suggested by the results in columns 1 and 2 in Table 11. For this reason we use the 2001 census for our benchmark estimates but the similarity of the results produced using the same set of instruments computed for different time periods, as in columns 2 and 3 of Table 11 supports the validity of our IV strategy.

Finally, in column 4 we adopt a common approach in migration studies (Altonji and Card, 1991), which consists in instrumenting current migration with its historical analog. In our case, such an approach amounts to using the percentage of immigrants in the block computed from the 2001 census, i.e. 9 years before our survey.[19] Results are in line with our main findings, namely the estimted coefficient is still negative and statistically significant.

The second robustness check, reported in Table 12, that we perform documents the importance of being able to observe the illegal migrants in our study. In column 1 we simply report our benchmark estimates from Table 9 for comparison. In column 2 we replicate the same model eliminating the indicator for illegal migrants from the control set (but still including such observations in the estimation). Results barely change, suggesting that the partially arbitrary assumptions made to identify legal and illegal migrants separately do not affect our main findings. Next, in columns 3 and 4 we eliminate from the sample the illegal immigrants as defined on the basis of two alternative definitions, so as to replicate results that could be produced with more standard surveys that only cover the legally resident population. Apparently, the uninstrumented estimates, reported in Panel A, change marginally while a more notable variation emerges in Panel B with IV results, which appear to be larger by 30% to 50%, depending on the specific definition of illegal migrant.

[insert Table 12 here]

5 A simple theoretical model

In this section we present a search model with double heterogeneity (in the supply of skills and in the demand for migrant workers) that is capable of generating equilibria that feature both positive sorting of immigrants in more segregated areas and, at the same time, lower employment in such areas, thus rationalizing both of our key empirical findings.

Typically positive sorting is unambiguously obtained only in the context of partial equilibrium analysis. General equilibrium models of the labor market with matching and sorting, instead, frequently feature multiple equilibria and in some such equilibria, the highly skilled self-select themselves into segregated areas. The model below is useful to illustrate the nature

[19] We also experimented with the same instrument computed from the 1991 census but at that time there were still very few immigrants in Italy and the instrument varies too little to generate statistically significant results.

of these sorting and matching equilibria and provides some intuition as to the sources of these multiple equilibria.

5.1 A simple matching model with endogenous sorting

Consider then that there is a measure one of migrant workers with heterogenous unobservable ability levels and two alternative residential locations. They can either move to segregated areas, where they have access to ethnic specific labor markets or they can go to non-segregated neighborhoods, where they have to pay a higher rent, but get access to the same labor markets as natives. In other words, the residential choice coincides with the choice of a labor market in which to search for jobs.

Throughout the analysis, we assume that natives are uniformly distributed across locations and are immobile. Obviously, this is merely a simplification assumption that can be relaxed and all our results would still hold as long as natives face higher mobility costs than migrants, which we consider to be a very reasonable assumption.[20]

Let the worker type be indexed by x, where x refers to (gross) labor market productivity and its value is drawn from a continuous cumulative distribution function F with support $[x_{min}, x_{max}]$. x is a fixed time invariant worker characteristic, with $x_{min} > 0$. Migrants are endowed with a unit of time and freely decide where it is optimal to locate and hence search for a job. There are two locations, n and s, which for convenience we label non-segregated and segregated, respectively. The non-segregated location are characterized by a per-period cost (rent) h_n, while residence in the segregated area is subject to a lower location cost h_s, i.e. $h_n > h_s$. Without loss of generality, we shall assume henceforth that $h_s = 0$, e.g. migrants live with friends or relatives.

We assume that the two locations also define two perfectly segmented labor markets, meaning that one can only work in one's same area of residence. This is also a simplifying assumption that can be easily relaxed without affecting our main qualitative results, as long as

[20] In the data we observe that the coefficient of variation of our the percentage of natives across census tracts is about twice as large as that of migrants.

searching and/or holding a job away from one's residential location is more costly that holding the same job close to home. Commuting costs are the obvious rational underlying this assumption.

Additionally, each labor market is internally imperfect and there are market frictions within each area. Following Pissarides (2000), assume that the meeting of migrants to jobs is regulated by a matching technology with constant returns to scale. Let u_s and u_n be the number of migrants searching in the segregated and non-segregated areas respectively, and v_s and v_n the number of vacancies posted in the two separate labor markets (at cost c_s and c_n per period).

Natives are randomly and uniformly distributed across locations so that their behavior does not affect differentially the matching technology of migrants across locations. Alternatively, one could also assume that the labor market is perfectly segmented also between natives and migrants, so that the two groups do not compete for the same jobs (Angrist and Kugler, 2003; Bodvarsson et al., 2008; Card, 1990, 2005; Friedberg and Hunt, 1995; Ottaviano and Peri, 2011).

The matching function in each area is indicated with:

$$m^l(u^l, v^l) \qquad l = n, s \tag{4}$$

with positive first derivatives and negative second derivatives. As in the traditional matching models with constant returns to scale, the job finding rate depends on the relative number of traders and is indicated with $\mu^l(\theta^l)$ with $\tilde{\mu}^l(\theta^l) = \frac{\partial \mu^l(\theta^l)}{\partial \theta_l} > 0$. where $\theta^l = \frac{v^l}{u^l}$ is a sufficient statistics for labor market conditions.

Due to matching frictions, successful matches in each area enjoy a pure economic rent, which is split according to a Nash bargaining rule, with migrants getting a fraction ρ of the total surplus. We assume, for simplicity, that ρ is identical in the two markets.

We solve the model in three steps. First we present the value functions and the asset equations, and define the key equilibrium conditions. Next, we solve the migrants' sorting behavior in partial equilibrium, taking as given the labor demand side and the job finding rate in each area. We then focus on job creation taking migrant behavior as given. Finally we discuss the general equilibrium of the model.

5.2 Asset value conditions

The value of a filled job in the non-segregated market with productivity x reads:

$$rJ^n(x) = x - w^n(x) + \lambda_n[V^n - J^n(x)] \tag{5}$$

where V^n is the value of a vacancy and r is the pure discount rate. Jobs are destroyed at the exogenous rate λ_n, and $w_n(x)$ is the wage rate.

The value of unemployment in the non-segregated area for a worker of type x is:

$$rU^n(x) = -h_n + \mu^n(\theta)[W^n(x) - U^n(x)] \tag{6}$$

where $W^n(x)$ is the value of the job for a type x. Similarly, the value of employment in the non-segregated labor market is:

$$rW^n(x) = w^n(x) - h_n + \lambda_n[U^n(x) - W^n(x)]. \tag{7}$$

Conditional on meeting a worker, at rate $q^n(\theta^n) = \frac{\mu^n(\theta^n)}{\theta^n}$, the employer gets the expected value of a job. In formula, its expression reads:

$$rV = -c_n + q^n(\theta^n)\left[E\left(J^n(z) \mid z \in \Omega^n\right) - V^n\right] \tag{8}$$

where the expectation is taken over the productivity distribution of workers who search in the non-segregated market, whose support is defined by Ω^n.

The value functions the segregated market are similarly defined. The main difference is that in the jobs in this market are destroyed at a higher rate than in the non-segregated market. The four value functions read:

$$
\begin{aligned}
rJ^s(x) &= x - w^s(x) + \lambda_s[V^s - J^s(x)] && (9)\\
rW^s(x) &= w^s(x) + \lambda_s[U^s(x) - W^s(x)] && (10)\\
rU^s(x) &= \mu^s(\theta^s)[W^s(x) - U^s(x)] && (11)\\
rV^s &= -c_s + q^s(\theta^s)\left[E\left(J^s(z) \mid z \in \Omega^s\right) - V^s\right] && (12)
\end{aligned}
$$

where Ω^s is the support of the productivity distribution of workers who search in the segregated areas.

Wages in each market and in each job are the outcome of a bilateral matching problem and workers get a fraction ρ of the total surplus, so that:

$$
\left[W^i(x) - U^i(x)\right] = \rho\left[W^i(x) - U^i(x) + J^i(x) - V^i\right] \qquad i = n, s \tag{13}
$$

Remember that for simplicity we have assumed that the fraction of the surplus is the same in both sectors.

5.3 Equilibrium

There are three key equilibrium conditions:

- Free entry and job creation in the non-segregated market (JC^n), which implies that the value of a vacancy be zero:

$$
V^n = 0 \tag{14}
$$

  This equation determines market tightness in the non-segregated market θ^n.

- Free entry and job creation in the segregated area (JC^s), which implies that the value of a vacancy be zero:

$$
V^s = 0 \tag{15}
$$

This equation determines market tightness in the segregated market θ^s.

- Workers' sorting ($Sort$) If we assume that migrants' sorting satisfies the reservation property, (a feature that holds in equilibrium) the labor supply is described by the marginal migrant with productivity R, where R is the productivity level for which the worker is indifferent between the two markets, so that:

$$U^n(R) = U^s(R) \tag{16}$$

Using the reservation property, the three key conditions become:

$$\mu^s(\theta^s)[W^s(R) - U^s(R)] = -h_n + \mu^n(\theta^n)[W^n(R) - U^n(R)] \tag{Sort}$$

$$\frac{c_n}{q^n(\theta^n)} = \frac{\int_R^{x^u} J^n(z)dF(z)}{1 - F(R)} \tag{JC^g}$$

and

$$\frac{c_s}{q^s(\theta^s)} = \frac{\int_{x_l}^R J^s(z)dF(z)}{F(R)} \tag{JC^b}$$

The first condition states that the marginal migrant is indifferent between locating in the non-segregated or in the segregated area. The second condition states that the total search costs in the non-segregated area are identical to the expected value of a job. The last condition has a similar interpretation, but refers to the segregated area. The system determines the three endogenous variables θ^n, θ^s and R.

The model is closed by determining the stock of workers into the four possible labor market states: unemployment and employment in each of the two areas. If we indicate with u^i the stock of unemployed migrants in each area and with e^i the stock of employed migrants, we have:

$$u^n + u^s + e^n + e^s = 1 \tag{17}$$

Workers' sorting implies that the share of workers in the segregated area is $F(R)$ while the remaining $1 - F(R)$ migrants search in the non-segregated area. The steady state unemployment condition in the two areas reads:

$$\mu^i(\theta^i)\, u^i = \lambda_i e^i \qquad i = n, s \tag{18}$$

where $e^s = F(R) - u^s$ and $e^n = 1 - F(R) - u^n$.

5.4 Partial Equilibrium: Supply-side

The surplus of a job in each sector is defined as the sum of the migrant's and employer's values of being on the job, net of the respective outside options, so that:

$$S^i(x) = J^i(x) - V^i + W^i(x) - U^i(x) \tag{19}$$

Using the value functions previously defined, as well as the free entry condition (which drives the value of a vacancy down to zero), the surplus of a match for a job in the non-segregated labor market with productivity x is:

$$(r + \lambda_n)S^n(x) = x - \mu^n(\theta^n)[W^n(x) - U^n(x)] \tag{20}$$

Recalling that wages get a fraction ρ of the total surplus, the previous expression reads:

$$S^n(x) = \frac{x}{r + \lambda_n + \rho\mu^n(\theta^n)} \tag{21}$$

with $\tilde{S}_n(x) = \frac{\partial S^n(x)}{\partial x} = \frac{1}{r+\lambda_n+\rho\theta^n q(\theta^n)}$.

Proceeding similarly, the surplus in the segregated market is:

$$S^s(x) = \frac{x}{r + \lambda_s + \rho\mu^s(\theta^s)} \tag{22}$$

In partial equilibrium, the job finding rates mu^i are constant, and the surplus from the job is an increasing linear function of the match specific productivity x. The surplus from the job can be used to obtain an expression for the value of unemployment, whose expression is given by:

$$U^s(x) = \frac{\mu^s(\theta^s)\rho x}{r + \lambda_s + \rho\mu^s(\theta^s)} \tag{23}$$

$$U^n(x) = \frac{\mu^n(\theta^n)\rho x}{r + \lambda_n + \rho\mu^n(\theta^n)} - h_n \tag{24}$$

Figure 4 shows the two value functions in partial equilibrium. The differences in the two curves are driven by the intercept (which is negative in the segregated area due to the location costs) and the slope. We make a key assumption in this respect:

- **Jobs destruction in the segregated market is sufficiently large**. We formally assume that

$$\lambda_s\mu^n - \lambda_n\mu^s + r(\mu^n - \mu^s) > 0 \tag{25}$$

  This implies that the value function of U^n is steeper than U^s, as in Figure 4.

[insert Figure 4 here]

The assumption above guarantees that the two value functions intersect, and that the reservation productivity value, R, defined below, is positive:

$$R = \frac{h_n(r + \lambda_s + \rho\mu^s)(r + \lambda_n + \rho\mu^n)}{\rho r(\mu^n - \mu^s) + \mu^n\lambda_s - \mu^s\lambda_n} \tag{26}$$

In this equilibrium jobs in segregated markets are occupied by migrants with low skills, as shown by Figure 4. Holding job creation constant, it is easy to show that an increase in job destruction rates in the segregated market reduces the reservation productivity inducing shifts of the most skilled migrants who are initially in the segregated areas to the non-segregated areas, while an increase of job destruction in the non-segregated market has the opposite effect.

$$\frac{\partial R}{\partial \lambda_n} = \frac{h_n(r+\lambda_s+\rho\mu^s)\left\{[\rho r(\mu^n-\mu^s)+\mu^n\lambda_s-\mu^s\lambda_s]+\mu^s(r+\lambda_n+\rho\mu^n)\right\}}{\left[\rho r(\mu^n-\mu^s)+\mu^n\lambda_s-\mu^s\lambda_n\right]^2} > 0 \quad (27)$$

Similarly an increase (reduction) in job finding rates in the non-segregated areas reduces (increases) the reservation productivity level. The opposite happens for an increase (reduction) of job finding rates in the segregated market. These effects are important in evaluating the consequences of congestion externalities associated with the presence of natives in the non-segregated market.

5.5 Partial Equilibrium: Labor Demand

To solve for job creation we need to evaluate the expected value of a job. We first focus on jobs in the non-segregated market. After an integration by parts, and making use of the sharing rule, the integral in equation JC^g can be written as

$$\begin{aligned}\int_R^{x^{max}} S^n(z)dF(z) &= S^n(x^{max}) - S^n(R) + (1-F(R))S^n(R) - \tilde{S}^n(R)\int_R^{x^{max}} F(z)dz \\ & \frac{\int_R^{x^{max}}(1-F(z))dz}{r+\lambda+\rho\theta^n q(\theta^n)} + \frac{(1-F(z))R}{r+\lambda+\rho\theta^n q(\theta^n)}\end{aligned}$$

so that the job creation condition is:

$$\frac{c_n[r+\lambda+\rho\mu^n(\theta^n)]}{q(\theta^n)(1-\rho)} = \frac{\int_R^{x^{max}}(1-F(z))dz}{1-F(R)} + R \quad (28)$$

Proceeding similarly for the expected value of jobs in segregated areas, the free entry condition reads:

$$\frac{c_s[r+\lambda+\rho\mu^s(\theta^s)]}{q(\theta^s)(1-\rho)} = R - \frac{\int_{x_{min}}^R F(z)dz}{F(R)} \quad (29)$$

Market tightness θ^i and the associated job finding rates μ_i depend on the various parameters, as well as on the migrants' sorting behavior. Most parameters have a direct effect on job creation, plus an indirect effect via the reservation productivity R. Formally, we can write:

$$\begin{aligned}\mu^n(\theta^n) &= \mu^n(R(.), r, \lambda_n, \rho))\\ \mu^s(\theta^s) &= \mu^s(R(.), r, \lambda_s, \rho))\end{aligned}$$

where the symbol $R(\cdot)$ suggests that now R is itself an endogenous variable. Notice that an increase in the reservation productivity R increases market tightness and the job finding rates in both markets. Indeed an increase in R improves the average quality of the workforce in both markets, so that firms naturally respond by posting more vacancies per unemployed. This result is important, and shows how sorting affects job creation. Formally, it is obtained by noting that $\frac{\partial\theta^n}{\partial R} > 0$ and $\frac{\partial\theta^s}{\partial R} > 0$ since:

$$\begin{aligned}\frac{C_n}{(1-\rho)}\frac{\rho\tilde{\mu}^n(\theta^n)q^n(\theta^n) - \tilde{q}^n(\theta^n)(r+\lambda+\rho\mu^n(\theta^n))}{q^n(\theta^n)^2}\frac{\partial\theta^n}{\partial R} &= \frac{f(R)\int_R^{x^{max}} F(z)dz}{(1-F(R))^2}\\ \frac{c_s}{(1-\rho)}\frac{\rho\tilde{\mu}^s(\theta^s)q^s(\theta^s) - \tilde{q}^s(\theta^s)(r+\lambda+\rho\mu^s(\theta^s))}{q^s(\theta^s)^2}\frac{\partial\theta^s}{\partial R} &= \frac{f(R)\int_{x^{min}}^{R} F(z)dz}{F(R)^2}\end{aligned}$$

where the left-hand-side is positive since $\tilde{q}^l(\theta^l) = \frac{\partial q^l(\theta^l)}{\partial\theta_l} > 0$, with $l = \{n, s\}$.

5.6 General Equilibrium

The general equilibrium of the model is obtained by solving for the triple R, θ^n, θ^s that simultaneously satisfy Sort JC^b and JC^g. One way to solve for the general equilibrium result is to analyze the migrants' sorting condition by explicitly considering the relationship between the job finding rates and the reservation productivity. This is equivalent to solving the following condition:

$$\frac{\mu^s(R,.)\rho R}{r+\lambda_s+\rho\mu^s(R,.)} = \frac{\mu^n(R,.)\rho R}{r+\lambda_n+\rho\mu^n(R,.)} - h_n \tag{30}$$

where the expression $\mu^s(R,.)$ and $\mu^n(R,.)$ are consistent with the job creation conditions. Both sides of the expression are increasing functions of R. The difference with respect to the partial equilibrium result is that the expressions for the value of unemployment in equations (30) are no longer simple linear functions, although they are still both increasing functions of R. There are two effects at work in this context.

- First, there is a positive *surplus effect*. This is analogous to the effect analyzed in partial equilibrium. An increase in R increases the value of unemployment in both sectors, but has a larger effect on the non-segregated market, as geometrically represented by the difference in the slope.
- Second, there is a *job creation* effect. An increase in R increases the job finding rate in both markets, since the average value of the workforce increases and more vacancies are posted.

As both effects reinforce each other in a non linear fashion, both sides are increasing and non linear functions of R. It follows that multiple equilibria are possible as in Figure 5. This is a typical feature of matching models with double heterogeneity (Albrecht and Vroman, 2002). In particular, we may have an equilibrium like at R_2 in the figure, where high productivity migrants enter the segregated sector.

[insert Figure 5 here]

In order to rule out multiple equilibria, the distribution of migrants by skill should be strongly concentrated at the lowest skill levels in order to prevent critical mass effects at the top of the skill distribution. These self-reinforcing effects may instead take place when migrants are uniformly distributed along the skill spectrum. This is because, as high skilled workers go to the segregated areas, vacancies increase dramatically in these areas. This labor demand effect explains the convexity in x of the value function associated with search for jobs in segregated areas.

By the same token, the fact that the most skilled go to the segregated areas reduces demand in the non-segregated areas making congestion externalities more important. This explains the concavity in workers' type of the value function associated with job search in the non-segregated sector. Both trading and congestion externalities would be lower if the distribution of workers types had been concentrated at the low end. Generally, we should expect to have multiple equilibria when the distribution of migrants by skill types has more dispersion.

5.7 Discussion and additional evidence

The existence in our model of multiple equilibria, among which some feature positive sorting of migrants into segregated areas, offers an explanation for one of our two key empirical findings, namely the larger (in absolute value) IV estimates compared the corresponding un-instrumented effects.

According to the results reported in Figure 5, positive sorting is more likely to occur among high skilled workers than low skilled workers. This is because the key general equilibrium mechanism that triggers positive sorting is the change in the average productivity of workers in each location that lead firms to modify their vacancy posting policy. Obviously, high skilled workers induce larger changes in average productivity when they move across areas than low skilled ones.

In order to empirically investigate this theoretical implication, in Table 13 we estimate the effect of residential segregation on employment for migrants of different educational levels. For ease of comparison, in column 1 we simply report our benchmark results from Table 9, while in following columns we replicate the same models restricting the sample to either high skilled migrants (column 2) or unskilled ones (column 3). These two groups are defined on the basis of self reported educational levels and we classify as high skilled all those who have at least a secondary school degree while all the others are low skilled. In Panel A we report un-instrumented results and in Panel B we show the corresponding IV estimates.

[insert Table 13 here]

Consistently with the predictions of the model, we find that for skilled migrants the un-instrumented estimate is positive and turns negative once instrumenting, a results that is clearly coherent with positive sorting. For unskilled migrants, we obtain results that are broadly in line with our benchmark.

The other key empirical finding that we documented in Section 4 is the negative effect of residential segregation on migrants' employment. In the model equilibrium employment depends on the job finding and job destruction rates. Specifically, the steady state condition is:

$$\lambda^l e^l = \mu^l(\theta^l)u^l \qquad l = \{n, s\} \tag{31}$$

And equilibrium employment can be written as a function of meeting and separation rates:

$$e^n = \frac{\mu^n(\theta^n)}{\mu^n(\theta^n) + \lambda^n} \tag{32}$$

$$e^s = \frac{\mu^s(\theta^s)}{\mu^s(\theta^s) + \lambda^s} \tag{33}$$

The informal hiring networks hypothesis suggests that

Notice that equations 32 and 33 show that, for given labor market conditions, i.e. holding θ constant, the job finding probability for migrants is higher in segregated than in non-segregated locations or $\mu^s(\theta) > \mu^n(\theta)$. As already mentioned, the evidence in Table A-3 in the Appendix is consistent with this hypothesis.

However, there are two more important elements that may lead to $e^s < e^n$ even in the presence of informal hiring networks. First, labor market conditions may be across locations. In particular, the labor market might be tighter in non-segregated areas or $\theta^n > \theta^s$, so that $\mu^s(\theta^s) < \mu^n(\theta^s)$. Such an instance would also be compatible with positive sorting, which appear to be relevant in our data, which implies that employers post more vacancies in the segregated location than elsewhere, $v^s > v^n$, as long as positive sorting is strong enough to also make $u^s > u^n$, i.e. enough workers move to the segregated location and loose the labor market. Notice that the relatively high level of education of migrants in our data (see the sample sizes in Table 13) appears to be consistent with this mechanism, i.e. positive sorting means that skilled workers move to the segregated location and since there are many of them it is likely that $u^s > u^n$. Additionally, in the model we also assume that job destruction rates are higher in the segregated location, i.e. $\lambda^n < \lambda^s$, which obviously also goes in the direction of lower employment in s than in n.

To conclude, the model can generate equilibria which show both key features of our data, i.e. positive sorting and lower employment in highly segregated locations, even maintaining assumptions that are compatible with the presence of informal hiring networks. Positive sorting can be rationalized with the general equilibrium reaction of labor demand to workers' mobility, especially of high skilled migrants. Lower employment in segregated areas is explained by either strong enough sorting effects, that lead to tighter labor markets in such areas or by differences in job destruction rates or both.

6 Conclusions

In this paper we used new survey data that cover both legal and illegal migrants in 8 cities in the North of Italy to estimate the effect of residential segregation on employment. Our analysis highlights two important empirical findings. First there appears to be positive sorting of migrants into the most segregated areas, as documented by the difference between instrumented and un-instrumented estimates. Second, residential segregation shows a negative and statistically significant effect on the employment probability of migrants.

Such a negative effect appears to be non-linear or, more specifically, it varies discontinuously around a key threshold value of 15-20% of migrants over the total local population. Below the threshold there is no statistically detectable effect, while a negative and significant impact of residential segregation emerges above the threshold.

We rationalize these results with a general equilibrium search and matching model with double heterogeneity which is capable of generating equilibria that feature both positive sorting of migrants into segregated locations as well as lower employment in such locations. Importantly, these results are compatible with a more efficient matching process in segregated areas, as implied by the popular informal hiring networks hypothesis and as also documented in our data.

From the policy perspective our results have far-reaching implications. On the one hand, the non-linearities in the effect of segregation on employment open the door to relocation policies aimed at improving overall employment rates, hence economic integration of migrants. However, the interpretation of the empirical evidence offered by our model suggests that residential segregation is a by-product of labor market segmentation and, in this sense, policies aimed at integrating different labor markets might be more effective and are certainly are not problematic as relocation policies in terms of enforcement. For example, lowering commuting costs by improving public transport or supporting the setup of informal community networks finding job opportunities for new immigrants by establishing a network of public employment services in segregated areas may allow migrants to find jobs in more distant locations from where they live.

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Tables

Table 1: Characteristics of the sampled cities

City	Size[a]	Income per capita[b]	Average age[c]	Unemployment rate[d]	Employment rate[d]
	[1]	[2]	[3]	[4]	[5]
Alessandria	93,676	13,648	46	0.065	0.45
Bologna	374,944	18,771	47	0.044	0.48
Brescia	190,844	15,812	45	0.048	0.48
Lucca	89,640	14,920	45	0.065	0.46
Milano	1,295,705	21,358	45	0.044	0.49
Prato	185,091	12,446	43[e]	0.057	0.51
Rimini	140,137	12,059	45[f]	0.070	0.46
Verona	265,368	15,220	44	0.049	0.48
Italy	60,045,068	12,953	43	0.112	0.43
Northern Italy[e]	27,390,496	15,529	44	0.049	0.49

[a] Number of residents. Source: ISTAT, 2009.
[b] Annual gross taxable income. Source: Tax declarations, 2007.
[c] Source: ISTAT, 2007.
[d] Source: ISTAT, 2001 Population Census.
[e] Source: City Population Register, 2005.
[f] Source: City Population Register, 2009.
[g] Norther Italy includes the following regions: Piemonte, Valle D'Aosta, Lombardia, Trentino Alto Adige, Veneto, Friuli Venezia Giulia, Liguria, Emilia Romagna.

Table 2: Shares of immigrants in the surveyed cities

	From population registers		From fRDB/EBRD survey		
	total in the city	only sampled neighborhoods	legal	illegal	total
	[1]	[2]	[3]	[4]	[5]
Alessandria	0.110	0.136	0.136	0.032	0.168
Bologna	0.090	0.098	0.098	0.011	0.109
Brescia	0.156	0.200	0.200	0.059	0.259
Lucca	0.079	0.092	0.092	0.013	0.105
Milano	0.140	0.165	0.165	0.021	0.186
Prato	0.137	0.178	0.178	0.027	0.205
Rimini	0.092	0.114	0.114	0.010	0.124
Verona	0.130	0.147	0.147	0.020	0.167

Table 3: Sampling structure

	Sampled blocks per district				Average obs
	Central	Mid-central	Peripheral	Total[a]	per block[b]
Alessandria	2	3	1	6 (23)	3.8 (140)
Bologna	2	5	7	14 (90)	6.2 (264)
Brescia	2	3	0	5 (30)	5.4 (242)
Lucca	2	2	6	10 (79)	4.6 (130)
Milano	4	8	19	31 (87)	6.5 (297)
Prato	0	2	4	6 (35)	2.8 (236)
Rimini	2	3	1	6 (57)	6.2 (242)
Verona	0	4	5	9 (23)	3.7 (225)
Total	14	30	43	87 (424)	5.4 (246)

[a] Total number of blocks in the city in parentheses.
[b] Average number of resident persons per block in parentheses.

Table 4: Comparison with other data sources

Variable	Survey		
	fRDB-EBRD[a]	LFS[b]	ISMU[c]
	[1]	[2]	[3]
Share of migrants	0.75	0.07	1.00
Share of migrants from NMS[d]	0.25	0.17	0.13
Share of migrants from Western Balcans[e]	0.25	0.19	0.17
Share of migrants other origins	0.25	0.63	0.70
1=illegal migrant	0.13	0.00	0.11
1=female migrants	0.47	0.51	0.51
1=no education	0.04	0.05	0.04
1=primary education	0.38	0.46	0.30
1=secondary education	0.48	0.39	0.45
1=tertiary education	0.10	0.10	0.21
1=employed	0.85	0.47	0.68

[a] These statistics refer to the whole sample (1,137 observations), not just to the sample used for the empirical results.

[b] The LFS data, being sampled from the population registers, only capture legal migrants. Moreover, it is not representative at the level of the single municipality and the reported data are restricted to the entire North of Italy.

[c] The ISMU data include both regular and irregular immigrants. It is based on 12,000 interviews conducted between October 2008 and February 2009 at popular social venues for migrants, such as language schools, assistance centers, et. The reported data are also restricted to the North of Italy.

[d] Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovak Republic and Slovenia.

[e] Albania, Bosnia, Croatia, Macedonia, Kosovo, Montenegro and Serbia

Table 5: Descriptive statistics

Variable	Mean [1]	Std. Dev. [2]	N [3]
Socio-demographic characteristics:			
Area of origin:			
New Member States (NMS)[a]	0.32	-	470
Western Balkans[b]	0.32	-	470
Other countries	0.37	0.48	470
Age	37.45	8.94	470
1=female	0.47	-	470
years living in Italy	8.94	5.25	470
Education:			
none	0.04	-	470
primary	0.39	-	470
secondary	0.46	-	470
tertiary	0.11	-	470
1=illegal immigrant	0.12	-	470
1=refused test	0.14	-	470
Language test score	481.92	88.2	470
1=owns (at least) one car	0.54	-	470
1=owns (at least) one mobile phone	0.99	-	470
1=internet at home	0.6	-	470
Labour market outcomes:			
1=employed	0.87	-	470
1=work on Sundays	0.31	-	397
1=found work through friends	0.59	-	398
Residential segregation (at the block level):			
% of non-Italians	16.58	10.37	470
% of immigrants from same origin	5.92	5.63	470

[a] Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovak Republic and Slovenia

[b] Albania, Bosnia, Croatia, Macedonia, Kosovo, Montenegro and Serbia

[c] The score of the test was normalized so that the average score is 500 with a standard deviation of 100.

Table 6: High and Low Segregated Immigrants

Variable	High segregation[a] [1]	Low segregation[a] [2]	Diff.[b] [3]
Age	39.595	36.751	2.843**
	(0.895)	(0.457)	(0.949)
1=female	0.465	0.466	-0.001
	(0.046)	(0.026)	(0.053)
Years since migration	8.207	9.184	-0.977*
	(0.431)	(0.288)	(0.560)
1=secondary education or more	0.629	0.548	0.081
	(0.045)	(0.026)	(0.052)
1=illegal migrant	0.077	0.135	-0.058*
	(0.025)	(0.018)	(0.031)
Language test score[c]	471.165	481.801	-10.640
	(10.632)	(5.141)	(10.659)
1=refused test	0.069	0.164	-0.095**
	(0.023)	(0.020)	(0.031)
1=owns (at least) one car	0.509	0.548	-0.039
	(0.046)	(0.026)	(0.053)
1=employed	0.905	0.861	0.044
	(0.027)	(0.018)	(0.032)
1=work on Sundays	0.365	0.296	0.068
	(0.047)	(0.027)	(0.054)
1=found work through friends	0.610	0.577	0.030
	(0.048)	(0.028)	(0.056)

The table reports means (standard deviations in partheses) of the indicated variable in the two samples.

[a] High- and low-segregated blocks are those where our measure of residential segregation lies in the top and bottom 25% of the observed distribution, respectively.

[b] The asterisks indicate the statistical significance of the difference in the means (or proportions) across the two samples. * significant at 10%; ** significant at 5%; *** significant at 1%.

[c] The score of the test was normalized so that the average score is 500 with a standard deviation of 100.

Table 7: Correlations of block characteristics

City	Correlation coefficients		
	Age of buildings[a]	Residential segregation[b]	
	vs.	vs	vs.
	Housing density[c]	Age of buildings[a]	Housing density[c]
	[1]	[2]	[3]
Alessandria	-0.719	0.332	-0.330
	(0.000)	(0.121)	(0.124)
Bologna	-0.673	-0.254	0.140
	(0.000)	(0.017)	(0.195)
Brescia	-0.270	0.515	-0.133
	(0.172)	(0.006)	(0.507)
Lucca	0.333	0.359	0.214
	(0.024)	(0.014)	(0.154)
Milano	-0.551	0.198	-0.163
	(0.000)	(0.005)	(0.021)
Prato	-0.700	-0.111	-0.254
	(0.002)	(0.670)	(0.325)
Rimini	-0.909	0.254	-0.303
	(0.000)	(0.129)	(0.068)
Verona	-0.308	0.125	-0.334
	(0.081)	(0.488)	(0.058)

P-values in paretheses.
[a] Average age of the buildings in the block.
[b] Percentage of immigrants in the block.
[c] Ratio of residential square meters per residential building in the block

Table 8: Immigrant characteristics across types of blocks

Variables	Age		1=Secondary educ. or more		1=Owns (at least) one car		Years since migration	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
New buildings[a]	0.154	0.243	0.012	0.027	-0.019	-0.029	0.649	0.666
	(0.84)	(0.84)	(0.06)	(0.06)	(0.05)	(0.03)	(0.41)	(0.53)
Dense housing[b]	-0.095	-0.026	-0.010	-0.036	0.161**	0.127	0.337	-0.113
	(1.48)	(1.32)	(0.06)	(0.06)	(0.06)	(0.07)	(0.53)	(0.70)
City fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
District fixed effects	yes	no	yes	no	yes	no	yes	no
Observations	470	470	470	470	470	470	470	470

Robust standard errors in parentheses clustered at the city level. * significant at 10%; ** significant at 5%; *** significant at 1%.
[a] 1=buldings in the block are older than average (within the city).
[b] 1=housing density in the block is higher than average (within the city).

Table 9: Probit regressions for employment

Variables	Dependent variable: 1=employed			
	Probit	Probit	IV-Probit[a]	IV-Probit[a]
	[1]	[2]	[3]	[4]
% of non-Italians in the block	-0.012*	-	-0.055**	-
	(0.007)		(0.026)	
% of immigrants from same origin in the block	-	0.002	-	-0.054
		(0.009)		(0.081)
Age	0.223***	0.223***	0.197***	0.210***
	(0.063)	(0.064)	(0.059)	(0.069)
Age squared	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
1=female	-0.573***	-0.540***	-0.543***	-0.480***
	(0.083)	(0.091)	(0.077)	(0.149)
1=primary education[b]	0.462	0.444	0.473	0.429
	(0.417)	(0.434)	(0.350)	(0.398)
1=secondary education[b]	0.357	0.342	0.378	0.329
	(0.513)	(0.520)	(0.456)	(0.478)
1=tertiary education[b]	-0.322	-0.313	-0.267	-0.371
	(0.413)	(0.421)	(0.356)	(0.413)
1=illegal immigrant	-0.602***	-0.592***	-0.575**	-0.593***
	(0.213)	(0.201)	(0.248)	(0.211)
Language test score[c]	0.002*	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
1=owns (at least) one car	0.386	0.355	0.365	0.315
	(0.255)	(0.236)	(0.264)	(0.271)
1=owns (at least) one mobile phone	0.701	0.660	0.882	0.657
	(0.565)	(0.598)	(0.584)	(0.538)
1=internet at home	-0.153	-0.144	-0.145	-0.152
	(0.294)	(0.299)	(0.270)	(0.291)
Average housing price	0.001**	0.000*	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Time to travel to city center[d]	-0.009	-0.013	-0.000	-0.008
	(0.009)	(0.009)	(0.015)	(0.013)
City fixed effects	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes
Observations	470	470	470	470
F-test excl. instruments	-	-	7920.14	15564.41

Robust standard errors in parentheses clustered at the city level. Additional controls: years since migration in Italy, dummy for non taking the language test, dummies for area of origin.

[a] Segregation is instrumented with the average age and average housing density of building in the block, both interacted with city dummies. The complete first stage results are reported in Table A-1.

[b] Omitted category: no education

[c] The test score is set to the mean score for individuals who refused to take it and the set of controls includes a dummy for not taking the test.

[d] Time to travel is measured in minutes by public transport.

Table 10: Probit regressions for employment with non-linearities

Variables	Dependent variable: 1=employed					
	[1]	[2]	[3]	[4]	[5]	[6]
PANEL A: Probit models						
% of non-Italians $[RS]$	0.026	-	-	-	-	-
	(0.017)					
% of non-Italians squared	-0.001**	-	-	-	-	-
	(0.000)					
$RS > 5\%$	-	0.104	-	-	-	-
		(0.141)				
$RS > 10\%$	-	-	0.119	-	-	-
			(0.085)			
$RS > 15\%$	-	-	-	-0.317***	-	-
				(0.076)		
$RS > 20\%$	-	-	-	-	-0.195	-
					(0.186)	
$RS > 25\%$	-	-	-	-	-	-0.245
						(0.184)
City fixed effects	yes	yes	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes	yes	yes
Observations	470	470	470	470	470	470
PANEL B: IV Probit models[a]						
$RS > 5\%$		-0.462	-	-	-	-
		(1.479)				
$RS > 10\%$		-	-0.718	-	-	-
			(0.550)			
$RS > 15\%$		-	-	-0.745	-	-
				(0.682)		
$RS > 20\%$		-	-	-	-1.917**	-
					(0.763)	
$RS > 25\%$		-	-	-	-	-0.935*
						(0.503)
City fixed effects		yes	yes	yes	yes	yes
District fixed effects		yes	yes	yes	yes	yes
Observations		470	470	470	470	470

Robust standard errors in parentheses clustered at the city level. Additional controls: age, age squared, gender, education, language test score, car ownership, mobile ownership, internet at home, time to travel to city center, years since migration in Italy, dummy for non taking the language test, dummies for origin (New member countries, Western Balkans, other origins).

[a] Segregation is instrumented with the average age and average housing density of building in the block, both interacted with city dummies.

Table 11: Estimates with different IV sets

Variables	Dependent variable: 1=employed			
Instruments:	Only housing density (2001)	Only housing age (2001)	Only housing age (1991)	Residential segregation in 2001[a]
	[1]	[2]	[3]	[4]
% of non-Italians in the block	-0.096***	-0.016	-0.015	-0.085***
	(0.025)	(0.023)	(0.030)	(0.015)
City fixed effects	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes
Observations	470	470	466	470
F-test excl. instruments	9327.92	1095.63	175.12	1930.81

Robust standard errors in parentheses clustered at the city level. Additional controls: age, age squared, gender, education, language test score, car ownership, mobile ownership, internet at home, time to travel to city center, years since migration in Italy, dummy for non taking the language test, dummies for origin (New member countries, Western Balkans, other origins).

[a] Percentage of non-Italians in the census tract computed from the 1991 census.

Table 12: Robustness check: illegal immigrants

Variables	Dependent variable: 1=employed			
	full sample	full sample no illegal imm control	only legal broad[a] definition	only legal narrow[b] definition
	[1]	[2]	[3]	[4]
PANEL A: Probit models				
% of non-Italians	-0.012*	-0.011	-0.012*	-0.012
in the block	(0.007)	(0.008)	(0.007)	(0.008)
City fixed effects	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes
Observations	470	470	381	366
PANEL B: IV Probit models[b]				
% of non-Italians	-0.055**	-0.056**	-0.079*	-0.100***
in the block	(0.026)	(0.022)	(0.042)	(0.031)
City fixed effects	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes
Observations	470	470	381	366

Robust standard errors in parentheses clustered at the city level. Additional controls: age, age squared, gender, education, language test score, car ownership, mobile ownership, internet at home, time to travel to city center, years since migration in Italy, dummy for non taking the language test, dummies for origin (New member countries, Western Balkans, other origins).

[a] Broad definition: for NON EU citizens illegal immigrants are those without a permit of stay or not answering to the question. For EU citizens illegal immigrants are those without a permit of stay or not answering to the question only if without a regular work (cannot register to local authorities).

[b] Narrow definition: NON EU citizens illegal immigrants if without a permit of stay. EU citizens always legal immigrants.

[c] Segregation is instrumented with the average age and average housing density of building in the block, both interacted with city dummies.

Table 13: Probit regressions for employment low high skilled immigrants

Variables	Dependent variable: 1=employed		
	All	High skilled[a]	Low skilled
	[1]	[2]	[3]
PANEL A: Probit			
% of non-Italians in the block	-0.012*	0.005	-0.028
	(0.007)	(0.016)	(0.040)
City fixed effects	yes	yes	yes
District fixed effects	yes	yes	yes
Observations	470	240	153
PANEL B: IV Probit[b]			
% of non-Italians in the block	-0.055**	-0.052**	-0.068***
	(0.026)	(0.027)	(0.026)
F-test excl. instruments	7920.14	1.26	4.53
City fixed effects	yes	yes	yes
District fixed effects	yes	yes	yes
Observations	470	240	153

Robust standard errors in parentheses clustered at the city level. Additional controls: age, age squared, gender, education, average housing price, language test score, time distance to city center, years since migration in Italy, dummy for non taking the language test, dummies for origin (New member countries, Western Balkans, other origins).

[a] Immigrants with at least secondary education.

[b] Segregation is instrumented with the average age and average housing density of building in the block, both interacted with city dummies.

Figures

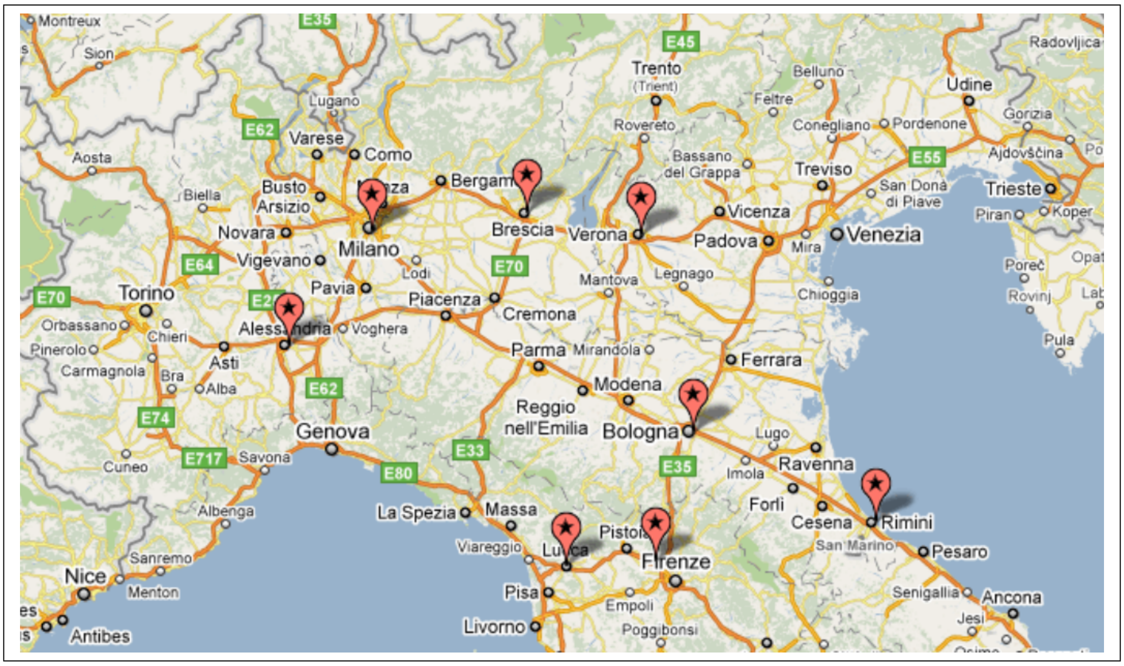

Figure 1: Surveyed cities

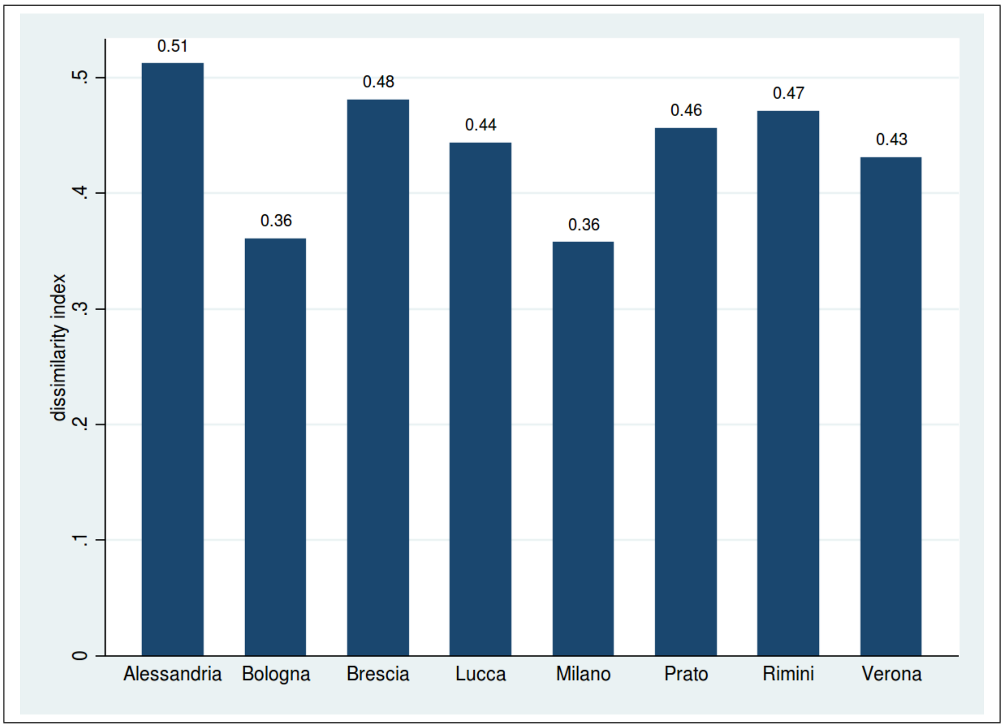

Figure 2: Dissimilarity indices

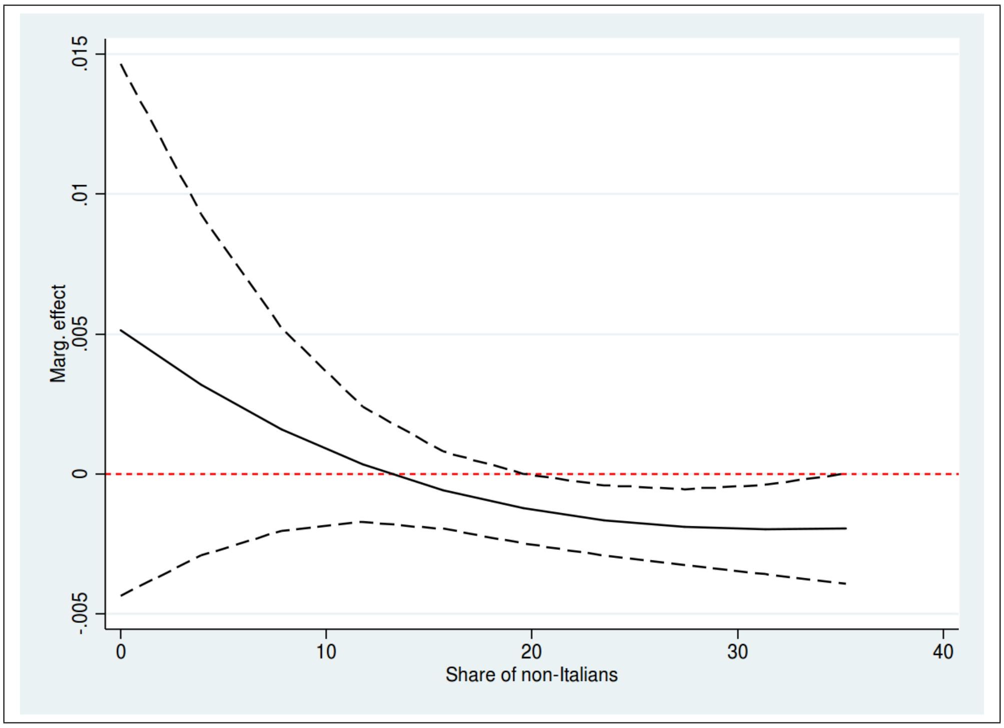

Figure 3: Quadratic effect of segregation on employment

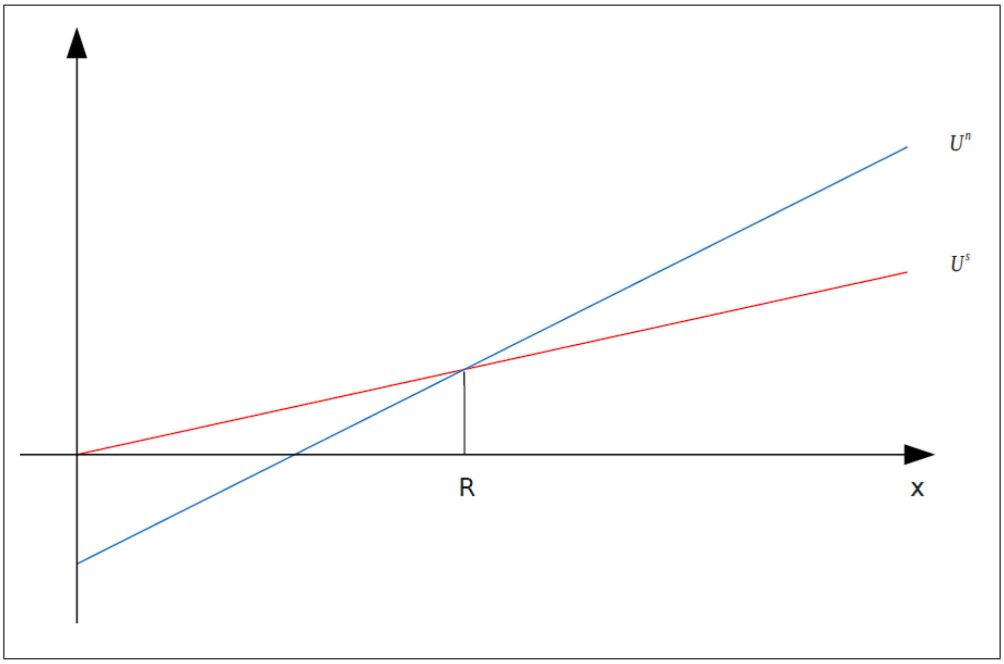

Figure 4: Sorting in partial equilibrium

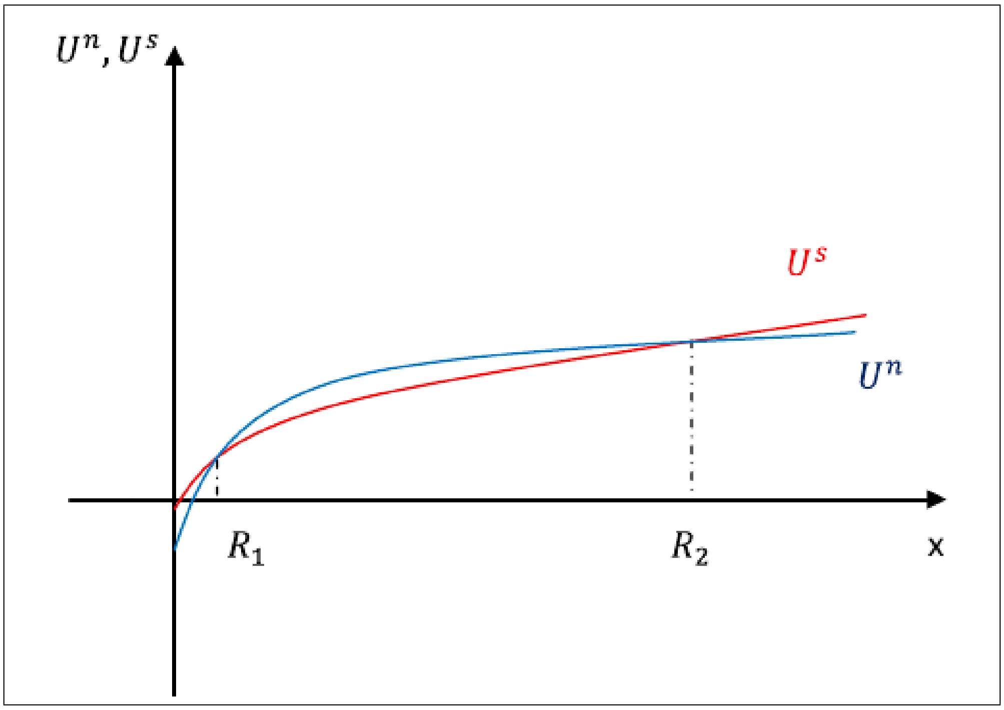

Figure 5: Sorting in general equilibrium

Appendix

Table A-1: First stage regressions

Variables	Segregation in the block:	
	% of non-Italians	% of migrants from same origin
	[1]	[2]
Housing age[a]	0.109	0.150**
	(0.099)	(0.043)
Housing age x Bologna	-0.199**	-0.265***
	(0.064)	(0.038)
Housing age x Brescia	0.163*	-0.021
	(0.071)	(0.047)
Housing age x Lucca	0.045	-0.093**
	(0.109)	(0.039)
Housing age x Milano	0.022	-0.091
	(0.125)	(0.054)
Housing age x Prato	-0.984***	-0.727***
	(0.133)	(0.048)
Housing age x Rimini	0.237	-0.097
	(0.151)	(0.114)
Housing age x Verona	0.031	-0.118**
	(0.093)	(0.046)
...		

Table A-1: First stage regressions (continued)

Variables	Segregation in the block: % of non-Italians	Segregation in the block: % of migrants from same origin
	[1]	[2]
...		
Housing density[b]	0.005	0.000
	(0.003)	(0.001)
Housing density x Bologna	-0.003	-0.001
	(0.002)	(0.001)
Housing density x Brescia	-0.005**	0.001
	(0.002)	(0.001)
Housing density x Lucca	-0.004	0.009
	(0.013)	(0.007)
Housing density x Milano	-0.006*	-0.001
	(0.003)	(0.002)
Housing density x Prato	-0.048***	-0.024***
	(0.005)	(0.003)
Housing density x Rimini	-0.022*	-0.014
	(0.009)	(0.008)
Housing density x Verona	-0.012***	-0.004***
	(0.002)	(0.001)
Average housing price	0.007	0.002
	(0.004)	(0.001)
City fixed effects	yes	yes
District fixed effects	yes	yes
Observations	470	470

Robust standard errors in parentheses clustered at the city level. Additional controls: age, age squared, gender, education, legal status, language test score, car ownership, mobile ownership, internet at home, time to travel to city center, years since migration in Italy, dummy for non taking the language test, dummies for origin (New member countries, Western Balkans, other origins). * significant at 10%; ** significant at 5%; *** significant at 1%.

[a] Average year of construction of the buildings in the block.

[b] Residential square meters over residential buildings in the block.

Table A-2: Employment and segregation for natives

Variables	Dependent variable: 1=employed		
	Probit	Probit	IV-Probit[a]
	[1]	[2]	[3]
% of non-Italians in the block	-0.022	-0.019	-0.034
	(0.016)	(0.020)	(0.031)
% of non-Italians squared	-	-0.000	-
		(0.001)	
Age	0.473***	0.473***	0.476***
	(0.098)	(0.100)	(0.096)
Age squared	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)
1=female	-0.931***	-0.928***	-0.881***
	(0.283)	(0.277)	(0.284)
1=primary education[b]	2.513***	2.504***	2.516***
	(0.742)	(0.753)	(0.658)
1=secondary education[b]	2.136**	2.126**	2.083**
	(0.906)	(0.903)	(0.824)
1=tertiary education[b]	2.837**	2.826**	2.827**
	(1.172)	(1.193)	(1.105)
1=owns (at least) one car	0.827***	0.828***	0.603***
	(0.298)	(0.300)	(0.164)
1=internet at home	-0.112	-0.110	-0.074
	(0.245)	(0.257)	(0.249)
Average housing price	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Time to travel to city center[c]	0.019***	0.019***	0.024***
	(0.006)	(0.006)	(0.008)
City fixed effects	yes	yes	yes
District fixed effects	yes	yes	yes
Observations	470	470	470
F-test excl. instruments	-	531.9	-

Robust standard errors in parentheses clustered at the city level. Additional controls: years since migration in Italy, dummy for non taking the language test, dummies for area of origin.

[a] Segregation is instrumented with the average age and average housing density of building in the block, both interacted with city dummies.

[b] Omitted category: no education

[c] Time to travel is measured in minutes by public transport.

Table A-3: Probit for jobs found through friends

Variables	Dependent variable: 1=jobs found through friends			
	Probit	Probit	IV-Probit[a]	IV-Probit[a]
	[1]	[2]	[3]	[4]
% of non-Italians in the block	0.022***	-	0.005	-
	(0.007)		(0.026)	
% of immigrants from same origin in the block	-	0.021	-	-0.019
		(0.016)		(0.031)
City fixed effects	yes	yes	yes	yes
District fixed effects	yes	yes	yes	yes
Observations	398	398	398	398

The sample is restricted to employed persons. Robust standard errors in parentheses clustered at the city level. Additional controls: age, age squared, gender, education, legal status, language test score, car ownership, mobile ownership, internet at home, time to travel to city center, years since migration in Italy, dummy for non taking the language test, dummies for origin (New member countries, Western Balkans, other origins).

[a] Segregation is instrumented with the average age and average housing density of building in the block, both interacted with city dummies.

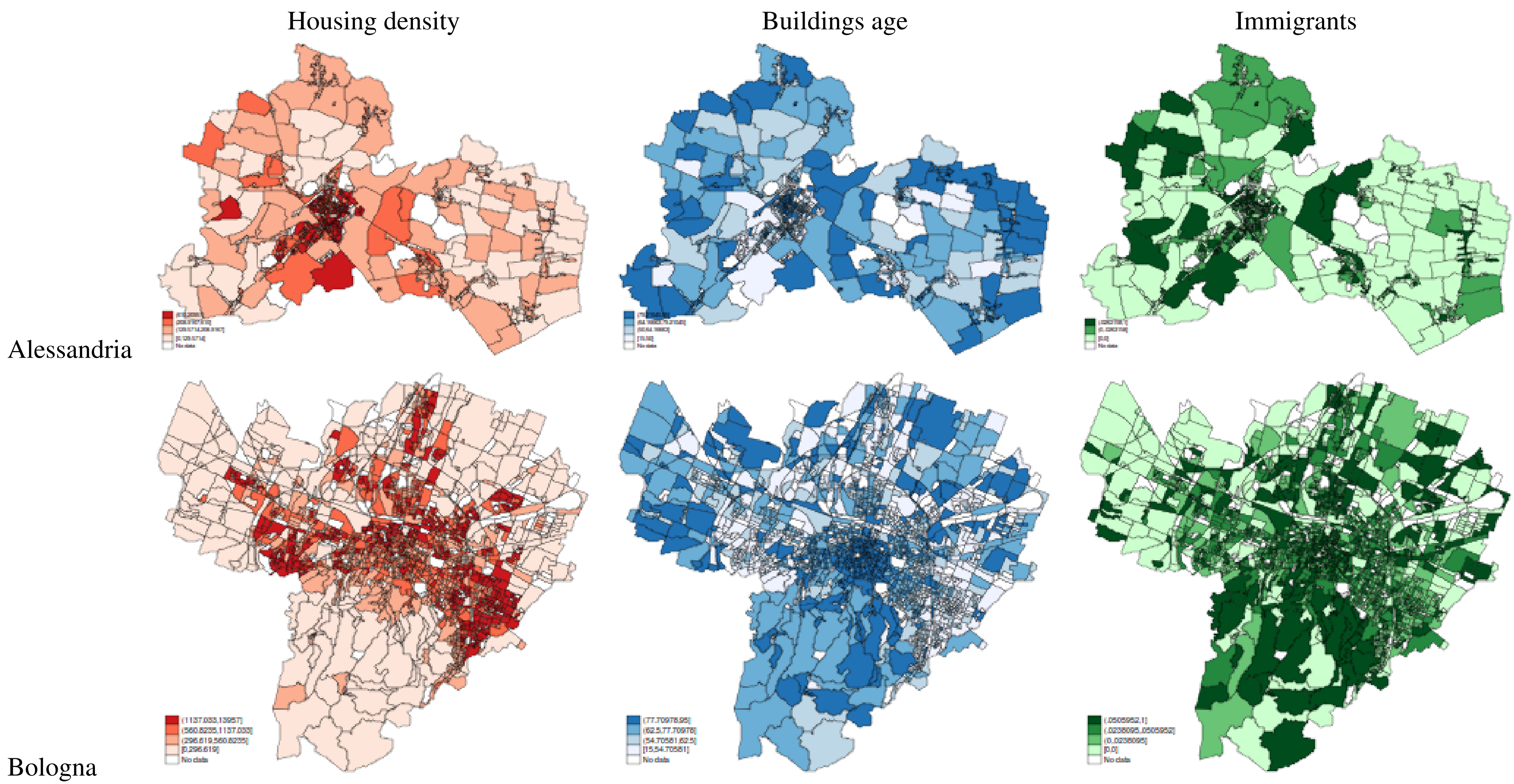

Figure A-1: Urban structure and immigrant population density

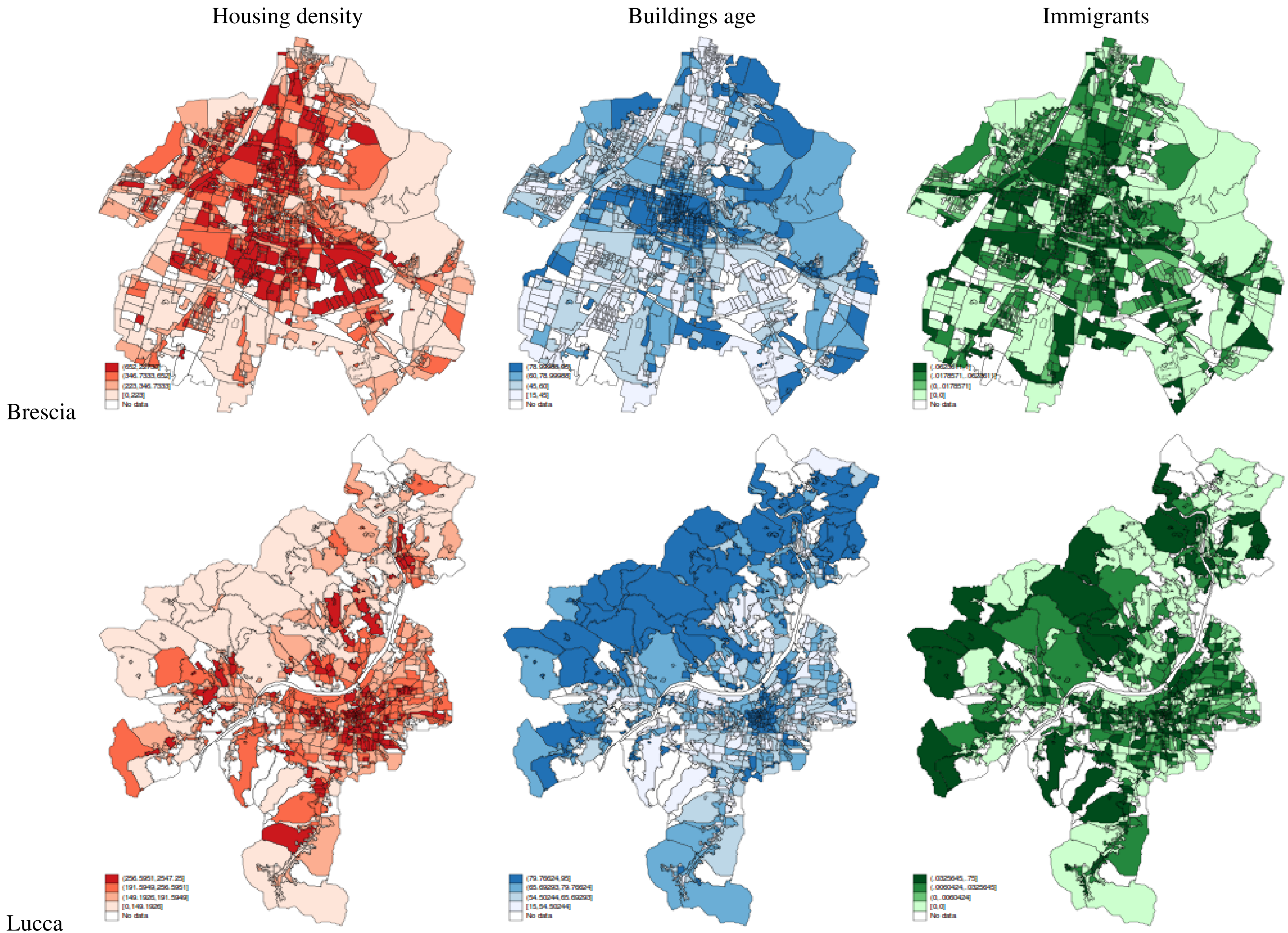

Figure A-1: Urban structure and immigrant population density (continued)

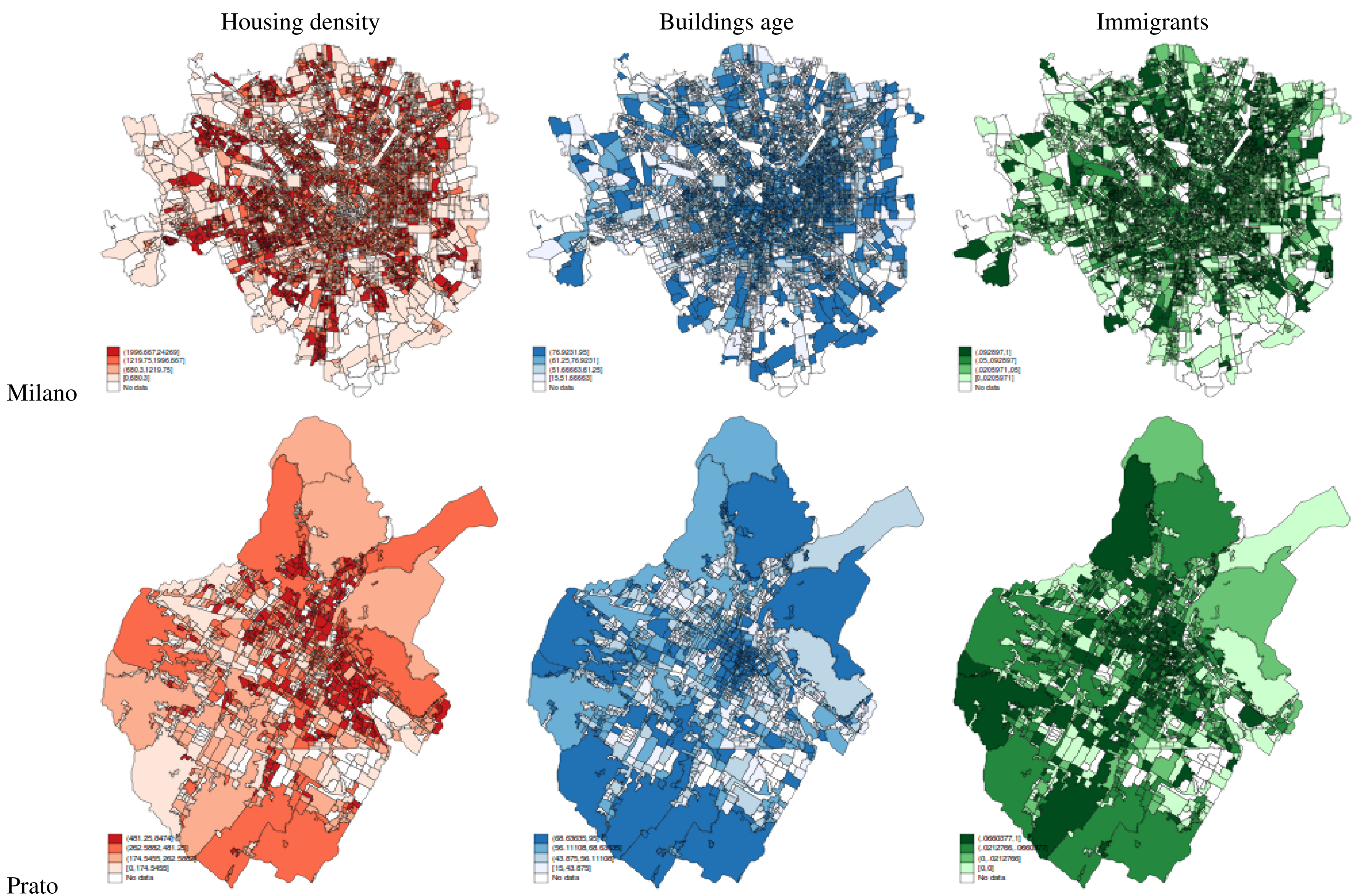

Figure A-1: Urban structure and immigrant population density (continued)

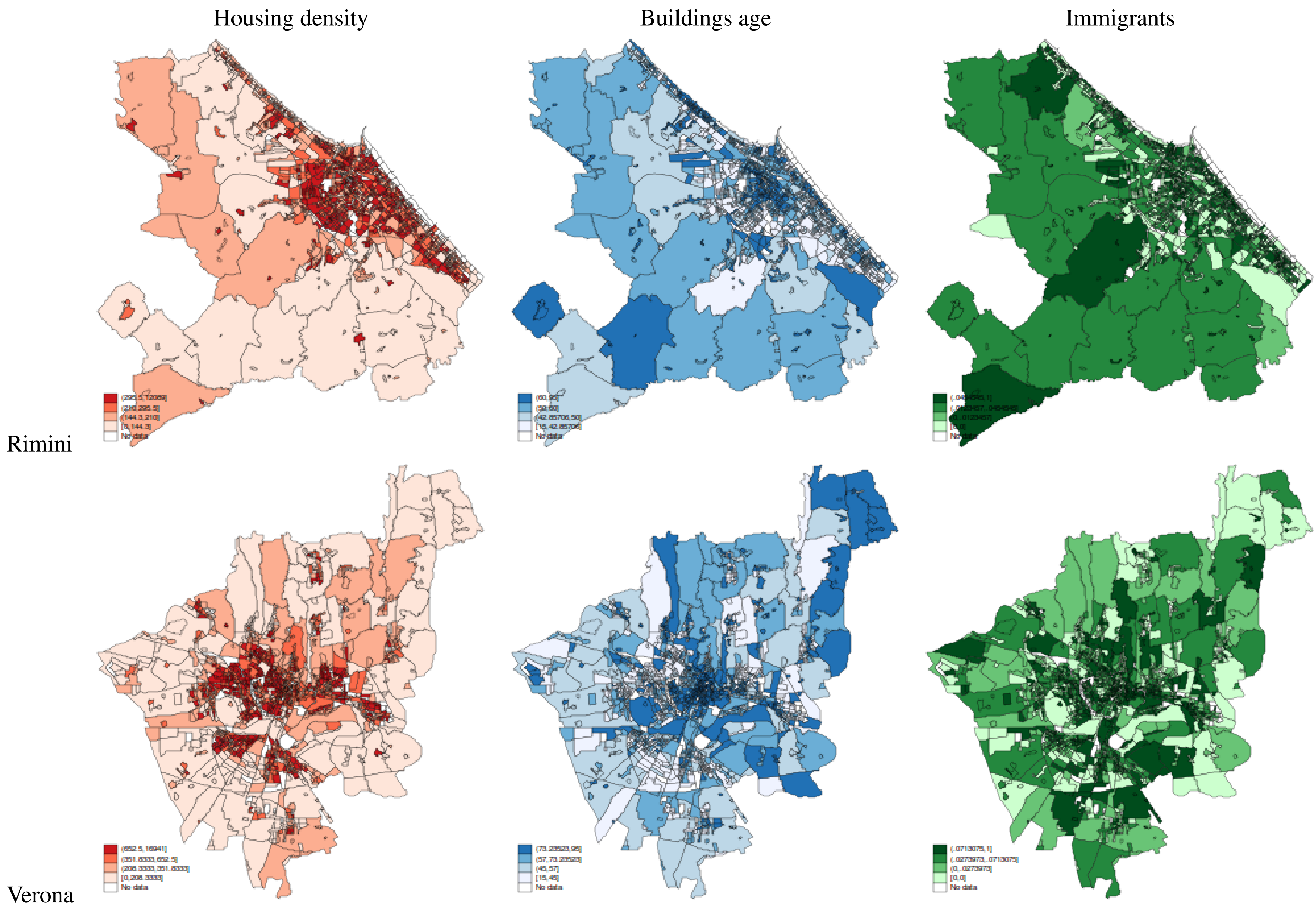

Figure A-1: Urban structure and immigrant population density (continued)