

# Don't stand so close to me: The urban impact of immigration

Antonio Accetturo, Francesco Minaresi  
Sauro Mocetti, Elisabetta Olivieri \*

Preliminary draft  
October 2011

**Abstract.** We examine the impact of immigration on residential market within urban areas. We develop a spatial equilibrium model that shows how the effect of an immigrant inflow in a neighborhood propagates to the rest of the city through changes in perceived local amenities and local prices. Predictions of the model are tested using a novel dataset on housing prices and population variables at the neighbourhood level for a sample of 20 main Italian cities. To address endogeneity problems we adopt an IV strategy which uses historical enclaves of immigrants across neighbourhoods to predict current settlements. We find that migration raises average housing prices at the city level; however reduces price growth in the neighbourhood affected by immigration vis-à-vis the rest of the city. This pattern is driven by the “native-flight” from immigrant intensive neighbourhoods towards other areas of the city. These findings are consistent with native preferences to live in predominantly native areas.

---

\* E-mail: [antonio.accetturo@bancaditalia.it](mailto:antonio.accetturo@bancaditalia.it), [manaresi@gmail.com](mailto:manaresi@gmail.com), [sauro.mocetti@bancaditalia.it](mailto:sauro.mocetti@bancaditalia.it) and [elisabetta.olivieri@bancaditalia.it](mailto:elisabetta.olivieri@bancaditalia.it). We thank David Card, Fernando Ferreira and Robert Helsley for useful discussions and suggestions, and conference participants at AIEL (Milan), SIEP (Pavia), and EALE (Cyprus). We are also indebted to municipal statistical offices for providing us with neighborhoods' data. The views expressed herein are our own and do not necessarily reflect those of Institutions with which we are affiliated.

## 1. Introduction

In April 2007 a local police patrol in Milan fined a Chinese shopkeeper while she was unloading her van in Via Sarpi – the oldest and biggest Chinatown of Italy – during business hour (according to the city regulations, unloading can be done early in the morning only). The woman reacted and in a few minutes several fellow countrymen surrounded the patrol and forced them to run off. For some hours, the Chinatown became a combat zone. In the following days, a huge debate was raised among media and politicians about the integration of the Chinese community in Italy. Riots and other violent disturbances are unfortunately quite common in several industrialized countries.<sup>1</sup> They are the outcome of several factors, with urban segregation being one of the most important. Indeed, if immigrants live isolated from natives, the social integration process is hampered and “local” social norms may become stronger.<sup>2</sup>

The aim of this paper is to provide a theoretical and empirical analysis of urban segregation dynamics, examining the impact of immigration on the housing market at the *intra-municipal* level. Needless to say, the residential market is a nice laboratory to identify spatial segregation and to analyze the role of preferences for living and socially interacting with people of different cultures, language, and ethnic backgrounds.

We develop a spatial general equilibrium model that formalizes how an immigrant shock in a neighbourhood propagates to the rest of the city, affecting rents and native mobility. We assume that natives give value to both housing rents and perceived amenities of the area in which they live, which is a function of the number of immigrants residing in the neighbourhood. Specifically, if natives’ perceived amenities of a neighbourhood are negatively (positively) influenced by the presence of immigrants, they may decide to out-migrate to (in-migrate from) other areas of the city. Therefore, the shift in the housing demand due to immigration might be offset (reinforced) by natives’ residential choices. Looking at house price growth in the neighbourhood hit by immigration relative to the city average allows for a clean identification of natives’ preferences towards living with immigrants. The identification of those preferences, on the contrary, is hindered if we solely look at the aggregate municipal level. Finally, we also allow for differential house supply elasticities between neighbourhoods. According to our theoretical results, (i) an immigrant shock to a neighbourhood increases the average price at the city level; (ii) the neighbourhood affected by the shock will have a higher (lower) house price growth with respect to the city average if and only if migrants have a positive (negative) effect on natives’ perceived amenities; (iii) natives’ mobility is affected by an income effect that

---

<sup>1</sup> Other examples include the Paris banlieus uprising in 2005 and the riots in the UK cities in 2011.

<sup>2</sup> According to Battu and Zenou (2010), residential segregation plays a crucial role for ethnic identity. Those who live in a high ethnic concentration area have a higher probability of rejecting the native culture.

induces them to move away from the area where immigrants settle, and an amenities effect whose sign depends on the effect of immigrants on local amenities; (iv) the negative (positive) impact of immigration on the house price growth is accentuated (attenuated) if immigrants concentrate in the neighbourhood with lower house supply elasticity.

The theoretical predictions are tested empirically using a unique dataset collecting information on migrants and natives, and housing prices at the neighbourhood level for a sample of 20 large Italian cities over the period 2003-2010. To identify the causal impact of immigration on house price dynamics within the city, we adopt an IV strategy. Our instrument, widely used in the literature on immigration, exploits historical enclaves of immigrants across neighbourhoods to predict current settlements (Card, 2001). Consistently with the theoretical prediction, we find that immigration has a positive effect on the average price growth at the municipal level. In particular a 10 percent increase in immigrant stocks raises average rents by 1.6 percentage points. If we look at the intra-municipal level, however, we find that an immigrant shock to a neighbourhood lowers house price growth with respect to the city average. According to our estimates, a 10 percent increase in immigrant population reduces housing prices by 2 percentage points vis-à-vis the city average. The price growth in neighbourhoods hit by immigration is even lower with respect to the rest of the city when immigrants settle in neighbourhoods where housing supply is more constrained (e.g. historical city centres). The negative dynamics in the housing market of immigrant-dense neighbourhoods is driven by the native-flight phenomenon: 10 additional immigrants that arrive in a neighbourhood cause 6 natives to re-settle in other areas of the city. All in all, these findings provide clean evidence of a deterioration of perceived local amenities and a growing spatial segregation of migrants.

Starting from the seminal work of Saiz (2003), several papers documented a positive effect of immigration on housing prices at the city level.<sup>3</sup> However, only two very recent papers move the analysis towards the intra-city level, allowing for heterogeneous effects across neighbourhoods. Saiz and Wachter (2011) focus on US metropolitan areas and use census waves to document that housing values have grown relatively more slowly in neighbourhoods of immigrant settlement. Sà (2011) find similar results for the UK cities over the period 2003-2010. She also finds that the negative impact is driven by the outflow of higher-income natives, which have larger financial means to escape from the perceived deterioration of local amenities. Compared with the previous papers we innovate on two main aspects. First, we provide a general equilibrium model which is able to replicate all the empirical findings. The model allows disentangling the impact of immigration on prices due to an increase in the housing demand from that due to a variation in perceived local amenities. Moreover, it also allows considering the role of different housing supply elasticities across neighbourhoods. Second, we provide novel evidence on the urban impact

---

<sup>3</sup> See Saiz (2003 and 2007) for the US, Gonzales and Ortega (2009) for Spain, De Blasio and D'Ignazio (2010) for Italy.

of immigration in a markedly different setting with respect to the US or UK. Indeed, Italy (and Europe as well) differs substantially from the US and UK in terms of attitudes towards immigrants. According to the World Value Survey, 12 percent of Italians mention people of different race as unwelcome neighbours against 4 percent of Americans. The percentages are 11 and 2 percent, respectively, in case of neighbours of different religion. According to our findings, those attitudes are the main drivers of house price adjustments within a city in response of an immigration shock.

Our paper is also related to the literature on urban segregation. Residential segregation has been investigated since the 50's in the sociological literature. In the last decades economists entered this field. Their attention was mainly driven by the economic consequences of ghettos – in term of economic performance of minorities, human capital accumulation and costly social behaviour (e.g. crime) – and by the determinants of segregation. On the latter point, Cutler et al. (1999) examine segregation in American cities and argue that in the past segregation was a product of collective actions taken by whites to exclude blacks from their neighbourhoods. However, by the 90's legal barriers were replaced by “decentralized racism”, that is whites pay more than blacks to live in predominantly white areas<sup>4</sup>. Most of the literature on urban segregation concerns the US whereas evidence for Europe is much more limited. On this respect, our paper provides evidence on urban segregation for a European country, shedding light on its potential determinants<sup>5</sup>.

The rest of the paper is organized as follows. In section 2, we develop the theoretical model and derive a set of testable predictions. In section 3 we describe the data and provide some descriptive analysis on urbanization patterns, house price dynamics and their relationship with immigrant settlements. In section 4 we present the empirical strategies adopted to test the theoretical findings. In section 5 we provide the results of the empirical analysis. Section 6 discusses robustness checks and extensions of our analysis. Section 7 concludes.

## 2. Theoretical model

### 2.1 Assumptions and equilibrium in the housing market

Suppose a city with 2 neighbourhoods, 1 and 2. Each individual  $i$  located in neighbourhood  $s$  maximizes the following utility function:

---

<sup>4</sup> Card et al. (2008) find that population flows exhibit tipping-like behavior: once the minority share in a neighborhood exceeds a “tipping point”, all white leave. Bayer et al. (2004) analyze segregation patterns in the San Francisco Bay Area and conclude that racial differences in socio-demographic characteristics explain a considerable amount of the observed segregation. See also Cutler et al. (2008).

<sup>5</sup> Also Boeri et al. (2011) examine residential segregation in Italy. They focus on the (negative) labor market consequences of immigrant segregation using data for 8 Italian cities.

$$U_{is} = A_s \frac{C_i^{1-\alpha} L_i^\alpha}{(1-\alpha)^{1-\alpha} \alpha^\alpha} \quad (1)$$

where  $A_s$  are the amenities in neighbourhood  $s$ ,  $C_i$  and  $L_i$  is the amount of, respectively, tradable good and housing consumed by  $i$ .

Assuming that the tradable good is the numeraire and income does not depend on location within the city, budget constraint is  $C_i + r_s L_i = Y_i$ , where  $r_s$  and  $Y_i$  represent, respectively, rents prevailing in area  $s$  and individual income.

Standard utility maximization leads to the following marshallian demands:

$$L_i^* = \frac{\alpha Y_i}{r_s} \quad (2)$$

$$C_i^* = (1-\alpha) Y_i \quad (3)$$

There are two types of workers: natives and immigrants. The total number of natives in the city is  $N$  a share  $\omega$  of which locates in area 1. Natives are free to move across neighbourhoods and their income is equal to  $Y$ . We assume that a mass  $m$  of immigrants locate in the city and concentrate in area 2. Immigrant income is equal to  $\gamma Y$ , with  $\gamma \in (0, 1]$ .

Aggregate housing demand for each area is therefore:

$$L_1^d = \omega N \frac{\alpha Y}{r_1} \quad (4)$$

$$L_2^d = [(1-\omega)N + \gamma m] \frac{\alpha Y}{r_2} \quad (5)$$

Housing supply in neighbourhood  $s$  is assumed to be equal to:

$$L_s^o = \beta_s r_s \quad (6)$$

Where  $\beta_s$  is the price elasticity of housing services. For the moment we assume that  $\beta = \beta_1 = \beta_2$ ; we will relax this assumption in the section 2.3.

Equilibrium prices are determined by the equations (4), (5) and (6):

$$r_1^* = \left( \omega N \frac{\alpha Y}{\beta} \right)^{\frac{1}{2}} \quad (7)$$

$$r_2^* = \left\{ [(1-\omega)N + \gamma m] \frac{\alpha Y}{\beta} \right\}^{\frac{1}{2}} \quad (8)$$

Natives are free to move across locations. This implies that in equilibrium the utility levels equalize across locations.

Due to Cobb-Douglas preferences indirect utilities are determined by the product between real wages and amenities. The natives' appreciation of local amenities is influenced by migration. On one hand, natives might have negative attitudes towards immigrants motivated by a taste for cultural homogeneity and by a racial or religious prejudice. Moreover, natives might be concerned by a deterioration of local standards of living due to an increase in crime or a crowding effect on local indivisible public goods (i.e. parks, transports, etc.). On the other hand, natives' perception of local amenities in response to migration can increase due to cultural diversity and a rise in the variety of local public goods (e.g. ethnic restaurants)<sup>6</sup>.

We assume that amenities in neighbourhood 1, unaffected by migration, are fixed and equal to  $A$ , while amenities in area 2 are a function of migration,  $A(m)$ , whose derivative depends on the balance between the above described forces.

The equalization between indirect utilities leads to the following equilibrium condition:

$$\frac{A}{(\omega N)^{\frac{\alpha}{2}}} = \frac{A(m)}{[(1-\omega)N + \gamma m]^{\frac{\alpha}{2}}} \quad (9)$$

Equilibrium area 1 share of natives is therefore:

$$\omega^* = \frac{N + \gamma m}{N} \phi(m) \quad (10)$$

where  $\phi(m) = \frac{A^{\frac{2}{\alpha}}}{A^{\frac{2}{\alpha}} + A(m)^{\frac{2}{\alpha}}} \in (0,1)$  represents the amenities effect of migration on

population location. The term  $\frac{N + \gamma m}{N}$  can be interpreted instead as a income effect, i.e. the crowding out of natives due to the increased demand of housing services by immigrants.

It is now possible to compute the city-level average rents and assess the effects of an inflow of immigrants. According to (7), (8) and (6), city level rents are equal to:

---

<sup>6</sup> See Mayda (2006) for an analysis on natives attitudes toward immigrants. For a discussion on the effects of cultural diversity see also Ottaviano and Peri (2006).

$$r^* = \frac{2}{\beta} \left[ \frac{(N + \gamma m) \alpha Y}{\phi(m) + [1 - \phi(m)]} \right]^{\frac{1}{2}} \quad (11)$$

## 2.2 Theoretical predictions

We can now assess the effects of migration on local rents, city level prices, and population.

**Result 1:** *Migration increases the average price at the city level.*

This can be easily obtained by deriving the log equation (11) by  $m$ :

$$\frac{\partial \ln r^*}{\partial m} = \frac{1}{2} \frac{\gamma}{N + \gamma m} \quad (12)$$

Equation (12) shows that the average city-level effect of immigration on prices is positive and depends on the income effects. This is a well-known result in the literature (Saiz, 2007): immigration generates an upward pressure on housing demand that generates an increase in rents whenever supply is not perfectly elastic.

**Result 2:** *The effects of migration on prices at the neighbourhood level also depend on amenities.*

This result can be obtained by deriving the log of equations (7) and (8) by  $m$ :

$$\frac{\partial \ln r_1^*}{\partial m} = \frac{1}{2} \left[ \frac{\gamma}{N + \gamma m} + \frac{\phi'(m)}{\phi(m)} \right] \quad (13)$$

$$\frac{\partial \ln r_2^*}{\partial m} = \frac{1}{2} \left[ \frac{\gamma}{N + \gamma m} - \frac{\phi'(m)}{1 - \phi(m)} \right] \quad (14)$$

Note that the income effect is the same in both areas, since the propagation of the migration shock from area 2 to area 1 is immediate due to the free mobility of natives. Income effect in area 1 is attenuated (emphasized) if migration increases (reduce) amenities in area 2. In other words, whenever migration generates a reduction in neighbourhood 2 amenities, native workers decide to migrate and pay higher rents in area 1 to “escape” foreigners. The effect on area 2 is just the opposite. Whenever immigrants deteriorate local amenities, housing costs in the area hit by migration grow less than the other areas of the city due to the native flight effect (i.e. larger residential migration from area 2 to 1).

**Corollary 1:** *The difference between neighbourhood and city trends solely depend on*

*amenities.*

This can be instantly obtained by subtracting (12) from (13) and (14):

$$\frac{\partial \ln r_1^*}{\partial m} - \frac{\partial \ln r^*}{\partial m} = \frac{1}{2} \frac{\phi'(m)}{\phi(m)} \quad (15)$$

$$\frac{\partial \ln r_2^*}{\partial m} - \frac{\partial \ln r^*}{\partial m} = -\frac{1}{2} \frac{\phi'(m)}{1-\phi(m)} \quad (16)$$

Equation (15) and (16) show that the local effects of immigration on rents solely depends on amenities. This is due to the fact that the income effect symmetrically propagates to the rest of the city, while the amenity effect is purely local. Equation (16) also shows that when immigrants decrease local amenities, prices tend to grow less in migration-intensive neighbourhoods, while the opposite occurs in areas less affected by migrants.

**Result 3:** *Migration generates pressures in the out-migration of natives.*

The relocation of native population to other neighbourhoods due to immigration, can be computed as:

$$\frac{\partial \omega^*}{\partial m} = \frac{\gamma}{N} \phi(m) + \frac{N + \gamma m}{N} \phi'(m) \quad (17)$$

The first term on the right-hand side represents the change in the income effect, that is always positive. Note that the larger the immigrants' income the stronger this effect and, therefore, the native flight. The second term is the amenities effects, which is positive whenever migration decreases perceived amenities in area (i.e.  $\partial A(m)/\partial m < 0$ ). In other words, the income effect is emphasized (attenuated) by the amenities effect whenever immigrants decrease (increase) local amenities in area 2.

### 2.3 Heterogeneous housing supplies

The previous framework can now be adapted to different space constraints across areas. This is particularly relevant as long as housing supply in some city centres (consider Rome or Venice, for example) is much more constrained than the one in sprawled peripheries. We now assume that  $\beta_1$  and  $\beta_2$  are different across locations.

Equations (7), (8) and (11) can now be rewritten as:

$$r_1^* = \left( \omega N \frac{\alpha Y}{\beta_1} \right)^{\frac{1}{2}} \quad (18)$$

$$r_2^* = \left\{ [(1-\omega)N + \gamma m] \frac{\alpha Y}{\beta_2} \right\}^{\frac{1}{2}} \quad (19)$$

$$r^* = 2 \left[ \frac{(N + \gamma m) \alpha Y}{\phi(m) \beta_1 + [1 - \phi(m)] \beta_2} \right]^{\frac{1}{2}} \quad (20)$$

$$\text{Where } \phi(m) = \frac{\frac{\beta_2^{\frac{2}{\alpha}}}{A^{\alpha}}}{\frac{A^{\frac{2}{\alpha}}}{\beta_2} + \frac{A(m)^{\frac{2}{\alpha}}}{\beta_1}} \in (0,1).$$

**Result 4:** If  $A > A(m)$ , when migration concentrates in the area with the most rigid housing supply, i.e.  $\beta_2 < \beta_1$ , and immigrants negatively affect natives' perceived amenities, rents in that area are likely to grow less than city average.

To see this point we take the analog of equation (16):

$$\frac{\partial \ln r_2^*}{\partial m} - \frac{\partial \ln r^*}{\partial m} = -\frac{1}{2} \left\{ \frac{\phi'(m)}{1 - \phi(m)} + \frac{(\beta_2 - \beta_1)\phi'(m)}{\phi(m)\beta_1 + [1 - \phi(m)]\beta_2} \right\} \quad (21)$$

Taking the derivative of (21) with respect to  $\beta_2$  we obtain  $\frac{\partial}{\partial \beta_2} \left( \frac{\partial \ln r_2^*}{\partial m} - \frac{\partial \ln r^*}{\partial m} \right) > 0$ . This

implies that if immigrants negatively (positively) affect natives' perceived amenities, their negative (positive) impact on neighbourhood housing price is larger (lower) when the housing supply of that area is more rigid.

### 3. Data and variables

We test our theoretical results using a novel dataset which matches demographic information and housing prices at the neighbourhood level for a sample of 20 main Italian cities. Our sample includes 5 out of the 6 largest Italian metropolitan areas (with more than 500,000 residents) and 35 percent of mid-sized cities (between 100,000 and 500,000

residents).<sup>7</sup>

As a neighbourhood, we consider an administrative district. For every district we use yearly data on the number of residents by nationality over the period 2000-10 coming from municipal statistical offices. Data on house prices are obtained from Agenzia del Territorio (AdT – the Italian Land Registry Office), and are available for the period 2003-10.<sup>8</sup> The AdT divides each Italian municipality into microzones (areas that are homogeneous in socioeconomic terms). For each microzone, we know housing price according to the types of house (villas and cottages, mansions, economic houses, typical houses) and the state of the building (poor, normal, and excellent). We restrict our observation to economic houses in normal conditions, which are those most frequently traded in the dataset. The matching between the two data sources has been executed using available geographical references in each source. Since the AdT data usually has a sharper partition into urban areas, the housing price at the district level has been computed as a weighted (population) average of microzones' prices. We end up with 1,128 observations broadly described in table 1.

Looking at the data, we find a clear evidence of an uneven distribution of immigrants across neighbourhoods. In Table 2 we report summary statistics for our sample of cities. In 2010, immigrants account for 13 percent of the total population in our sample of cities, above the national figure (7,5 percent). Moreover, the difference in the fraction of foreigners between the most and the less immigrants intensive areas is considerable, more than 13 percentage points on average. Between 2003 and 2010, the fraction of immigrants over population raised from 6.6 to 13 percent. In many cities, this increase in immigrant stock has not been homogenous across neighbourhoods. A commonly used index to measure the evenness of the distribution across neighbourhoods is the dissimilarity index. It indicates the fraction of population that should be moved from one area to the other to get a homogeneous distribution of migrants and natives across neighbourhoods (Duncan and Duncan, 1955; Cutler et al. 2008).<sup>9</sup> The higher the index, the more segregated the city. According to this index, residential segregation has somewhat increased in Milan, Naples and Padua and, in the second half of the decade, also in Rome and Venice, whereas it has decreased in Bologna, Florence and Turin (see Figure 1).

In the same years the increase in real estate values has been substantial: between

<sup>7</sup> Specifically, the sample includes Genoa, Milan, Naples, Rome and Turin among large metropolitan areas and Bergamo, Bologna, Brescia, Florence, Modena, Novara, Padua, Prato, Reggio-Emilia, Trento, Trieste, Udine, Venice, Verona and Vicenza among mid-sized cities. In these municipalities is concentrated about 16 percent of Italian population and 25 percent of immigrant population. The distribution of the cities across geographical areas broadly reflects that of the immigrant population in Italy.

<sup>8</sup> This database provides information on real estate market for the whole national territory. Data are collected exploiting several sources: bill of sales, assessments of real estate agencies and specialized magazines, and estimates of AdT.

<sup>9</sup> Formally, the index for a municipality  $i$ , composed by neighborhoods  $n \in [1, \dots, N]$  is computed as follows:

$$DI_i = \frac{1}{2} \sum_{n=1}^N \left| \frac{\text{immigrants}_{in}}{\text{immigrants}_{i,tot}} - \frac{\text{natives}_{in}}{\text{natives}_{i,tot}} \right|$$

2003 and 2010 the yearly house price growth was in our sample of cities is, on average, 3.2 percent in nominal terms. Price growth is substantial until 2007 and remains basically flat later. As shown in Figure 2a, immigration is positively correlated with the contemporaneous housing boom<sup>10</sup> at the city level. However, the uneven distribution of immigrants within the city might lead also to divergent dynamics across neighbourhoods. In Figure 2b we computed house price and immigrant population growth at the neighbourhood level. Growth rates have been computed as deviation from the average growth rate in the city to control for any omitted shock at city level and common to all its neighbourhoods. The sign of the correlation coefficient, in contrast with the previous case, is negative. This means that the house price growth in the neighbourhood hit by immigration is relatively lower with respect to the city average.

These correlations are in line with the theoretical results when immigrants lower natives' perception of local amenities. By the way, they are at best only suggestive as they might reflect spurious correlation or reverse causation. In the following empirical section we deal with these issues.

## 4. Empirical strategy

In this section we develop a set of empirical models to test the theoretical results of Section 2.

### 4.1 Testing the predictions

*Testing result 1* – The result 1 of the theoretical model predicts that an inflow of immigrants would raise the average housing price at the city level. To test this prediction we use the following linear specification:

$$\log P_{n,c,t} = \alpha + \lambda \log M_{n,c,t-1} + CITY_c + YEAR_t + \mu_{n,c,t} \quad (22)$$

where  $n$ ,  $c$  and  $t$  indicate neighbourhood, city and year, respectively. The dependent variable  $P$  is the housing price in the neighbourhood  $n$ , and  $M$  is the number of immigrants, as measured at the end of previous year. We include city fixed effects to control for time invariant heterogeneity among cities and year dummies to take into account for the housing business cycle. Although the unit of analysis of equation (22) is the neighbourhood, the estimate of  $\lambda$  indicates the effect of immigration at city level. This is achieved by weighting each observation with the share of municipal population in each neighbourhood at the beginning of the period of observation. In this way, we weight more the areas with

---

<sup>10</sup> According to De Blasio and D'Ignazio (2010), immigration inflows push up rents and housing prices in the destination cities. Similar evidence has been found also for other countries.

the larger population, that is those that influence more the average prices at city level.

*Testing result 2 and Corollary 1* – According to the theoretical predictions, if immigrants increase (decrease) local amenities, then their inflow should raise (lower) house prices in the neighbourhood vis-à-vis the city average. To identify this phenomenon, we use the following model:

$$\log P_{n,c,t} = \alpha + \delta \log M_{n,c,t} + (CITY_c \times YEAR_t) + DISTRICT_{n,c} + \varepsilon_{n,c,t} \quad (23)$$

Compared with the previous specification, we now include neighbourhood fixed effects and the interaction between city level and annual fixed effects. The first set of dummies aims at capturing time-invariant neighbourhood's characteristic which are likely to affect both the price levels and the location of migrants. The second set aim at partialling-out city-year specific trends.<sup>11</sup> The estimated coefficient for  $\delta$  is the effect of immigration on the difference between local and average housing prices. Corollary 1 shows indeed that its sign is the effect of immigrants on amenities (i.e. netting out the income effect); a positive sign would imply that immigrants improve natives' perception of local amenities, while if the sign is negative would indicate a deterioration in the natives' amenities.

*Testing result 3* – An inflow of immigrants into a neighbourhood generates two effects on native mobility. The first is the income effect which unambiguously pushes out natives from the area affected by the immigrant inflow. The second is the amenity effect: it opposes the income effect if immigrants improve local amenities, while it reinforces it if immigrants decrease amenities.

The effect of immigration on native mobility *within* city boundaries is estimated by the empirical model:<sup>12</sup>

$$N_{n,c,t} = \alpha + \rho M_{n,c,t} + (CITY_c \times YEAR_t) + DISTRICT_{n,c} + \xi_{n,c,t}. \quad (24)$$

That is identical to equation (24) with the exception of the dependent variable, that is the number of native individuals in the neighbourhood  $n$ , in city  $c$ , at time  $t$ .

<sup>11</sup> Notice that we consider only official immigrants. However, the presence of unofficial immigrants would not bias our estimates if they are proportional to official immigrants and the constant of proportionality depends on time-invariant neighborhoods' characteristics and city-per-year trend variables (which we control for) plus a stochastic term (Bianchi et al. 2011).

<sup>12</sup> In model (24) both migrants and natives are measured in *levels*. There are two reasons for this choice: first, the resulting estimate can be interpreted straightforwardly as the number of natives that move in response to the arrival of one additional migrant; second, the native stock is much bigger than the migrant one (on average it is ten-times bigger). As a result a one percentage raise in immigrants is likely to affect only marginally native stocks in percentage terms.

*Testing result 4* – The theoretical model predicts heterogeneous effects depending on the relative elasticity of housing supply in the area affected by immigration vis-à-vis the rest of the city. In particular, if immigration decreases local amenities, the negative effect will be stronger if the neighbourhood affected by the shock is characterized by a more rigid house supply.

To test this mechanism, we slightly modify the equation (23) by adding an interaction term between the number of migrants in the area and a dummy variable equal to one if the neighbourhood has a rigid housing supply ( $B_{n,c}$ ):

$$\log P_{n,c,t} = \alpha + \sigma \log M_{n,c,t} + \theta \log M_{n,c,t} * B_{n,c} + (CITY_c \times YEAR_t) + DISTRICT_{n,c} + \omega_{n,c,t} \quad (25)$$

Since we do not have information on the actual price elasticity of housing supply, we proxy it by distinguishing between “bounded neighbourhoods” (i.e., neighbourhoods that are completely surrounded by other municipal districts) and peripheral ones. “Bounded neighbourhoods” are therefore the historical city centres, that are usually constrained in the supply of new buildings by the presence of city regulations for the preservation of historical areas.

## 4.2 Identifying causal effects

A simple OLS estimator is likely to yield inconsistent estimates of  $\lambda$ ,  $\delta$ ,  $\rho$ , and  $\sigma$  and  $\theta$  of equations (22)-(25) due to omitted variable or reverse causality biases. For example, the construction of a new transportation facility could lead to both a change in the prices and the inflow of immigrants in a certain area, thus leading to inconsistent estimates (omitted variable bias); alternatively, immigrants usually tend to settle in cheaper areas, thus implying that the relation between immigration and prices could be reverted (reverse causality).

In order to overcome these problems, we use a Two-Stage-Least-Squares (2SLS) strategy exploiting a standard “shift-share” instrument. This methodology is based on the idea that immigrants tend to settle in places where immigrants from the same country already reside (Card, 2001). Therefore, we predict the composition of neighbourhood’s immigrant population on the basis of the distribution of immigrants in 1991 by origin country.

Specifically, for each neighbourhood  $n$ , we compute a fictional number of migrants:

$$S_{n,c,t} = \sum_i \pi_{i,n,c,t_0} M_{i,t} \quad (26)$$

where  $\pi_{i,n,c,t_0}$  measures the fraction of immigrants from country  $i$  that were settled in the

neighbourhood  $n$  of the city  $c$  in 1991;<sup>13</sup>  $M_{i,t}$  is the total number of immigrants from the same country in Italy at time  $t$ . Then, for instrumenting  $M_{c,t}$ , we simply sum over neighbourhoods:  $S_{c,t} = \sum_n S_{n,c,t}$ .

The assumption that this prediction is independent of time- and neighbourhood-specific shocks driving current housing prices is based upon two reasonable considerations. First, the immigrant inflow in 1991 is not driven by omitted variables which are likely to affect prices in the future. This assumption is fulfilled since immigrants at the beginning of the nineties were few and it is quite unlikely that their presence could influence future rents. Second, our instrument is not valid if all immigrants moved to the same neighbourhood; in this limiting case, it would be impossible to disentangle local and national flows and the instrument could be identical to the endogenous variable. This is not the case in our dataset: foreign population in the cities of the sample represents the 25 percent of total foreigners in Italy. Moreover, the neighbourhood with the largest number of immigrants (District 1 in Rome) counted in 2010 around 40,000 immigrants, that is less than 1 percent of the total immigrant population in Italy.

Another threat to identification is represented by possible violations of the stable unit-treatment value assumption (SUTVA). This can occur in both the first and the second stage of the IV estimate. The violation of SUTVA in the first stage occurs when the 1991 stock of immigrants in neighbourhood  $n$  is correlated also with the *current* location of migrants in neighbourhood  $m$ . This would represent a possible violation of the exclusion restriction for the instrument, thus leading to inconsistent IV estimates. The SUTVA violation in the second stage occurs when an exogenous inflow of immigrants in a neighbourhood affect amenities in the nearby neighbourhoods and, as a consequence, prices. In both cases identification of the effects of immigration would not be possible. In section 6.1 we test for this violation of the SUTVA by including spatial lags of  $M_{n,c,t}$  in model (23). In particular, we add to our baseline the average of log immigrants in adjacent neighbourhoods and we instrument this additional (endogenous) regressor with the spatial lag of the instrument described in (26).

## 5. Results

Table 3 presents the results of model (22). Using the OLS estimator (first column), we fail to identify a significant effect at any conventional level. However, IV estimates reveal a positive and significant effect of migration on average house prices at the city level. According to this result, a 10 per cent increase in the stock of immigrants (that

---

<sup>13</sup> In some cases these shares are computed in the middle of the 90s instead of 1991 because of data availability.

roughly represents the annual average growth in the period of observation) would raise the average house price by 1.6 per cent. In the same period of time the housing prices growth averaged at 3 per cent. Thus, back of the envelope calculations show that more than half of the price growth over the period has been driven by the increase in the immigrant population.

The comparison between OLS and IV shows that there is an attenuation bias in the OLS estimates. This may be due to either reverse causality or omitted variables. For example, low housing prices in the city are likely to attract new migrants, thus generating attenuation in the city-level estimates. Demographic trends may also play an important role as omitted variables. The presence of a large ageing population is likely to both create a downward pressure on prices and attract new migrants specialized in eldercare, thus attenuating the OLS results.

IV estimates are consistent with the previous literature on immigration and housing prices; according to the model this coefficient can be interpreted as an income effect, that is the consequence of the increased housing demand (due to migration) in the presence of an imperfectly elastic housing supply.

Table 4 shows the OLS and IV estimates of model (23). As explained in the previous section, the estimated coefficient of interest (i.e. the difference between the local and city-average price growth rates) can be interpreted as the effects of migration on perceived local amenities by natives. Both OLS and IV specifications reveal that prices tend to grow significantly slower than the average in the neighbourhoods where immigrants settle. In particular, according to IV estimates, a 10 per cent increase in immigrant population decreases local prices by nearly 2 percentage points with respect to the city average. This implies that immigration deteriorates natives' perceived quality of life.

According to the model, if foreigners lower local amenities we should observe that the number of natives in an area should decrease in response to migration. We can provide direct evidence of this. Table 5 reports results of model (25): while the spurious OLS correlation between migrants and natives is never statistically significant, causal IV estimates show that 10 additional immigrants in a neighbourhood above the city-year average induces 6 natives to relocate in other areas of the city.<sup>14</sup>

Finally, we test the theoretical Result 4 by estimating model (26). Given the fact that housing supply is more rigid in the central areas than in peripheries, the income effect should be greater and, thus, price growth should react more intensively to migration inflows in "bounded neighbourhoods". Indeed, Table 6 shows that the negative price dynamics due to immigrant inflows are stronger in neighbourhoods with more rigid housing supply. Even as far as demographic dynamics are concerned, the differential

---

<sup>14</sup> It should be noted that migration does not generate a native relocation outside the city. IV estimates on the effect of migration on the total number of natives in the city are never statistically significant. This is also consistent with the evidence on Italy by Mocetti and Porello (2010).

natives' outflow is stronger when immigrants settle in more rigid housing supply areas (table 7). When immigrants settle in the city centre, 10 more immigrants lead to a differential drop-out of almost 7 natives against 4 in the non-bounded neighbourhoods. Both these results are consistent with our theoretical predictions.

## 6. Robustness and extensions

### 6.1 The SUTVA assumption

As explained in section 4.2, the estimates of effects at a very local level can generate a violation of the SUTVA both in the first and second stage of regressions. In order to cope with this problem, we introduce spatial lags in model (23). Results are displayed in table 8.

In the first stages of this IV regression we can observe that the effect of the lagged instrument on the number of immigrants is not significant different from zero. Thus, immigration in 1991 does not affect current immigration in the nearby neighbourhoods of the city.

In the second stage, we find that results in table 5 are very robust: again, a 10 percent increase in immigrant population reduces house prices by nearly 2 percentage points vis-à-vis the city average. Furthermore, the number of immigrants in close neighbourhoods has not any significant effect on local prices.

According to these results, the stable unit-treatment value assumption does not seem to be violated in our IV baseline specification in both the first and second stages.

### 6.2 Immigration and house price distribution at the city level

The urban impact of immigration does not concern only larger urban areas. Indeed, immigrants are more geographically spread over the territory than they were in the past and one might doubt whether previous findings are generalizable to all Italian municipalities. Unfortunately, we do not have information on immigrant distribution across neighbourhoods for all Italian municipalities. Nevertheless, we are still able to build indicators of price distribution at the municipal level (such as minimum price, average and maximum price) and to correlate these indicators with immigration measured at the same level<sup>15</sup>.

Empirically, we run a regression with city price indicators and log of immigrants, both measured at the municipal level:

---

<sup>15</sup> We consider only municipalities with at least 5,000 residents and two AdT microzones to examine the differential price dynamics within cities above a minimum size threshold.

$$PI_{c,t} = \alpha + \beta \log M_{c,t} + CITY_c + YEAR_t + \varepsilon_{c,t} \quad (27)$$

where  $PI_{c,t}$  is a price indicator varying by municipalities ( $c$ ) and year ( $t$ ); we use different price indicators: log of price in the most expensive neighbourhood, log of mean price, log of price in the cheapest neighbourhood.  $M_{c,t}$  is the municipal stock of immigrants in year  $t$ . Finally we include year dummies and fixed effects at the municipal level. To address endogeneity we exploit again enclaves. Namely, we use immigrants' settlements across municipalities in 1995 to predict current settlements.<sup>16</sup>

Results are reported in Table 9. We get a positive effect of immigration on the mean price: according to IV estimates, a 10 percent increase in immigrants raises house prices on average by 3.4 percent. More importantly for our purposes, we do find a differential impact across neighbourhoods. Namely the same increase in immigrant stock lead to a 3.8 percent price growth in the most expensive neighbourhoods and to a 2.7 percent price growth in the cheapest ones. Therefore, immigrant population growth causes a relatively slower housing price appreciation in poorer neighbourhoods, thus leading to a widening of price differential within the city. These findings mirror those obtained with the analysis at the neighbourhood level.

## 7. Conclusions

The aim of this paper was to provide evidence of the dynamics and the effects of urban segregation of immigrants.

To do so, we analyse the effect of immigration on housing market and on native mobility at the *intra-municipal* level exploiting the fact that the residential market is an ideal laboratory to analyse the interplay between immigrants and natives within the city.

We first provide a theoretical guidance to the empirics showing that the effects of migration on prices at neighbourhood level are solely driven by natives' perceived changes in their quality of life. These changes also influence the spatial distribution of natives within the city.

The empirical evidence on 20 large Italian shows that a 10 percent increase in immigrant stocks at neighbourhood level reduces housing prices by 2.0 percentage points vis-à-vis the city average. Moreover, the arrival of 10 migrants generates the outflow (to other areas of the city) of 6 natives. These results are robust to a number of checks first by verifying the possible violation the SUTVA hypothesis, and then by extending the analysis to measures of price distribution of all Italian municipalities.

All in all, our results seem to suggest that immigration generates a clear deterioration

---

<sup>16</sup> The past distribution of immigrants by country and municipalities was provided by Istat.

of perceived local amenities by natives. This leads to increasing urban inequality in the real estate market. Moreover, this induces a sizable redistribution of natives within the city with a growing spatial segregation of migrants, thus suggesting potential difficulties in the integration process.

## References

- Battu, H and Y. Zenou (2010), Oppositional identities and employment for ethnic minorities: evidence from England, *Economic Journal*, 120: F52-F71.
- Bayer, P., R. McMillan and K.S. Rueben (2004), What drives racial segregation? New evidence using Census microdata, *Journal of Urban Economics*, 56: 514-535.
- Bianchi, M., P. Buonanno and P. Pinotti (2011), Do immigrants cause crime? *Journal of the European Economic Association*, forthcoming.
- Boeri, T., M. De Philippis, E. Patacchini and M. Pellizzari (2011), Moving to segregation: Evidence from 8 Italian cities, mimeo.
- Card, D. (2001), Immigrant inflows, native outflows, and the local labor market impacts of higher immigration, *Journal of Labour Economics*, 19: 22-64.
- Card, D., A. Mas and J. Rothstein (2008), Tipping and the dynamics of segregation, *Quarterly Journal of Economics*, 123: 177-218.
- Cutler, D.M., E.L. Glaeser and J.L. Vigdor (1999), The rise and decline of the American ghetto, *Journal of Political Economy*, 107: 455-506.
- Cutler, D.M., E.L. Glaeser and J.L. Vigdor (2008), Is the melting pot still hot? Explaining the resurgence of immigrant segregation, *Review of Economics and Statistics*, 90: 478-497.
- De Blasio, G. and A. D'Ignazio (2010), The impact of immigration on productivity: evidence from the Italian real estate market, mimeo.
- Duncan, O.B. and B. Duncan (1955), A methodological analysis of segregation indexes, *American Sociological Review*, 20: 210-217.
- Gonzales, L. and F. Ortega (2009), Immigration and housing booms: evidence from Spain, mimeo.
- Mayda, A.M. (2006), Who is against immigration? A cross-country investigation of individual attitudes toward immigrants, *Review of Economics and Statistics*, 88: 510-530.
- Mocetti S. and C. Porello (2010), How does immigration affect native internal mobility? New evidence from Italy, *Regional Science and Urban Economics*, 40: 427-439.
- Ottaviano G.I.P. and G. Peri (2006), The economic value of cultural diversity: Evidence from US cities, *Journal of Economic Geography*, 6: 9-44.
- Sa, Filipa (2011), Immigration and house price in the UK, IZA discussion paper 5893.
- Saiz, A. (2003), Room in the kitchen for the melting pot: immigration and rental price, *Review of Economics and Statistics*, 85: 502-521.
- Saiz, A. (2007), Immigration and housing rents in American cities, *Journal of Urban Economics*, 61: 345-371.

Saiz, A. and S.M. Wachter (2011), Immigration and the neighborhood, *American Economic Journal: Economic Policy*, 3: 169-188.

Schelling, T.C. (1969), Models of segregation, *American Economic Review*, 59: 488-493.

## Tables

Table 1: summary statistics

|                      | Mean  | Standard deviation | 25 <sup>th</sup> percentile | 50 <sup>th</sup> percentile | 75 <sup>th</sup> percentile |
|----------------------|-------|--------------------|-----------------------------|-----------------------------|-----------------------------|
| Number of immigrants | 5,317 | 5,809,1            | 1,581                       | 2,922                       | 7,218                       |
| Housing price        | 2,317 | 948,6              | 1,631                       | 2,099                       | 2,724                       |

Authors' elaboration on data from municipal administrative archives and AdT.

Table 2: demographic statistics

| City          | Number of districts | Population per district in 2010 | Immigrants over population in 2003 |                                       |                                       | Immigrants over population in 2010 |                                       |                                       |
|---------------|---------------------|---------------------------------|------------------------------------|---------------------------------------|---------------------------------------|------------------------------------|---------------------------------------|---------------------------------------|
|               |                     |                                 | City average                       | In more intensive immigrants district | In less intensive immigrants district | City average                       | In more intensive immigrants district | In less intensive immigrants district |
| Bergamo       | 7                   | 17,242                          | 7.7                                | 11.4                                  | 4.1                                   | 15.0                               | 19.1                                  | 6.0                                   |
| Bologna       | 9                   | 42,231                          | 5.7                                | 7.6                                   | 3.7                                   | 12.7                               | 17.1                                  | 10.4                                  |
| Brescia       | 5                   | 39,410                          | 10.0                               | 16.4                                  | 6.2                                   | 17.9                               | 23.4                                  | 12.0                                  |
| Florence      | 5                   | 74,398                          | 7.7                                | 13.3                                  | 4.7                                   | 13.5                               | 19.5                                  | 9.6                                   |
| Genoa         | 9                   | 67,549                          | 5.5                                | 9.3                                   | 2.2                                   | 8.3                                | 14.5                                  | 3.1                                   |
| Milan         | 9                   | 146,972                         | 8.5                                | 12.1                                  | 6.9                                   | 16.4                               | 24.3                                  | 13.0                                  |
| Modena        | 4                   | 46,166                          | 7.6                                | 15.9                                  | 5.5                                   | 14.7                               | 25.9                                  | 11.8                                  |
| Naples        | 10                  | 99,375                          | 1.7                                | 4.3                                   | 0.3                                   | 3.0                                | 6.3                                   | 0.7                                   |
| Novara        | 5                   | 21,005                          | 5.2                                | 9.0                                   | 3.1                                   | 12.5                               | 21.4                                  | 6.5                                   |
| Padua         | 8                   | 26,768                          | 6.6                                | 9.4                                   | 4.4                                   | 14.4                               | 22.7                                  | 9.7                                   |
| Prato         | 5                   | 37,571                          | 7.4                                | 14.1                                  | 5.4                                   | 15.1                               | 28.3                                  | 10.2                                  |
| Reggio-Emilia | 8                   | 21,236                          | 8.3                                | 18.9                                  | 4.2                                   | 17.0                               | 30.9                                  | 10.9                                  |
| Rome          | 19                  | 151,243                         | 7.1                                | 18.6                                  | 3.4                                   | 11.9                               | 32.1                                  | 6.5                                   |
| Turin         | 10                  | 90,857                          | 7.3                                | 12.8                                  | 3.5                                   | 14.2                               | 21.2                                  | 8.3                                   |
| Trento        | 8                   | 14,537                          | 4.9                                | 8.5                                   | 2.0                                   | 11.2                               | 20.1                                  | 3.9                                   |
| Trieste       | 7                   | 29,803                          | 4.9                                | 9.0                                   | 1.8                                   | 8.7                                | 16.7                                  | 2.1                                   |
| Udine         | 7                   | 14,232                          | 6.2                                | 9.0                                   | 4.5                                   | 13.5                               | 16.9                                  | 10.3                                  |
| Venice        | 12                  | 22,574                          | 3.8                                | 5.7                                   | 0.7                                   | 10.8                               | 17.7                                  | 1.9                                   |
| Verona        | 8                   | 32,967                          | 7.2                                | 11.5                                  | 3.3                                   | 13.9                               | 20.5                                  | 5.6                                   |
| Vicenza       | 7                   | 16,555                          | 9.2                                | 13.4                                  | 6.9                                   | 16.0                               | 19.3                                  | 12.2                                  |
| <b>Mean</b>   | <b>8</b>            | <b>50,635</b>                   | <b>6.6</b>                         | <b>11.5</b>                           | <b>3.8</b>                            | <b>13.0</b>                        | <b>20.9</b>                           | <b>7.7</b>                            |

Authors' elaboration on data from municipal administrative archives.

\* Figures on immigrants for Genoa refer to 2005 instead of 2003; for Naples refer to 2008 instead of 2010.

Table 3: Impact of immigration on price growth at the city level

| Dependent variable: Log of house price | OLS              | IV                  |
|--|------------------|---------------------|
| Log of immigrants                      | 0.034<br>(0.036) | 0.160***<br>(0.053) |
| City fixed effects                     | YES              | YES                 |
| Year fixed effects                     | YES              | YES                 |
| First stage F-statistics               | -                | 51.6                |
| Number of observations:                | 1,128            | 1,128               |

City price is defined as weighted population average of neighborhoods' price. Heteroskedasticity-robust standard errors clustered at the city and year level.

Table 4: Impact of immigration on price growth at the neighbourhood level

| Dependent variable: Log of house price | OLS                  | IV                   |
|--|----------------------|----------------------|
| Log of immigrants                      | -0.105***<br>(0.025) | -0.195***<br>(0.048) |
| Neighborhood fixed effects             | YES                  | YES                  |
| City $\times$ year fixed effects       | YES                  | YES                  |
| First stage F-statistics               | -                    | 25.2                 |
| Number of observations:                | 1,128                | 1,128                |

Heteroskedasticity-robust standard errors clustered at the city and year level.

Table 5: Impact of immigration on native population growth at the neighbourhood level

| Dependent variable: Natives      | OLS              | IV                   |
|----------------------------------|------------------|----------------------|
| Immigrants                       | 0.230<br>(0.276) | -0.564***<br>(0.134) |
| Neighborhood fixed effects       | YES              | YES                  |
| City $\times$ year fixed effects | YES              | YES                  |
| First stage F-statistics         | -                | 12.2                 |
| Number of observations:          | 1,128            | 1,128                |

Heteroskedasticity-robust standard errors clustered at the city and year level.

Table 6: Impact of immigration on price growth in neighbourhoods  
with different supply elasticity

| Dependent variable: Log of house price   | OLS                  | IV                   |
|--|----------------------|----------------------|
| Log of immigrants                        | -0.114***<br>(0.024) | -0.215***<br>(0.049) |
| Log of immigrants × bounded neighborhood | -0.051**<br>(0.022)  | -0.072*<br>(0.038)   |
| Neighborhood fixed effects               | YES                  | YES                  |
| City × year fixed effects                | YES                  | YES                  |
| First stage F-statistics                 | -                    | 29.2<br>59.5         |
| Number of observations:                  | 1,128                | 1,128                |

Heteroskedasticity-robust standard errors clustered at the city and year level.

Table 7: Impact of immigration on native population growth in neighbourhoods  
with different supply elasticity

| Dependent variable: Natives       | OLS                | IV                   |
|-----------------------------------|--------------------|----------------------|
| Immigrants                        | 0.273<br>(0.425)   | -0.423***<br>(0.161) |
| Immigrants × bounded neighborhood | -0.0513<br>(0.324) | -0.256**<br>(0.106)  |
| Neighborhood fixed effects        | YES                | YES                  |
| City × year fixed effects         | YES                | YES                  |
| First stage F-statistics          | -<br>-             | 50.7<br>9.1          |
| Number of observations:           | 1,128              | 1,128                |

Heteroskedasticity-robust standard errors clustered at the city and year level.

Table 8: Impact of immigration on price growth including spatial lags

|  | IV  |  |
|--|---|--|
| <i>1<sup>st</sup> stage</i>                      | Dependent variable:<br>Log of immigrants  | Dependent variable:<br>Log of immigrants<br>(spatially lagged) |
| Log of instrument                                | 0.751***<br>(0.150)                       | -0.317<br>(0.605)  |
| Mean of the log of instrument (spatially lagged) | -0.003<br>(0.003)                         | 0.637***<br>(0.084)  |
| Neighborhood fixed effects                       | YES                                       | YES  |
| City × year fixed effects                        | YES                                       | YES  |
| First stage F-statistics                         | 12.52                                     | 28.81  |
| <i>2<sup>nd</sup> stage</i>                      |   |  |
|  | Dependent variable:<br>Log of house price |  |
| Log of immigrants                                | -0.194***<br>(0.048)                      |  |
| Mean of the log of immigrants (spatially lagged) | 0.000<br>(0.001)                          |  |
| Neighborhood fixed effects                       | YES                                       |  |
| City × year fixed effects                        | YES                                       |  |
| Number of observations:                          | 1,128                                     |  |

Heteroskedasticity-robust standard errors clustered at the city and year level.

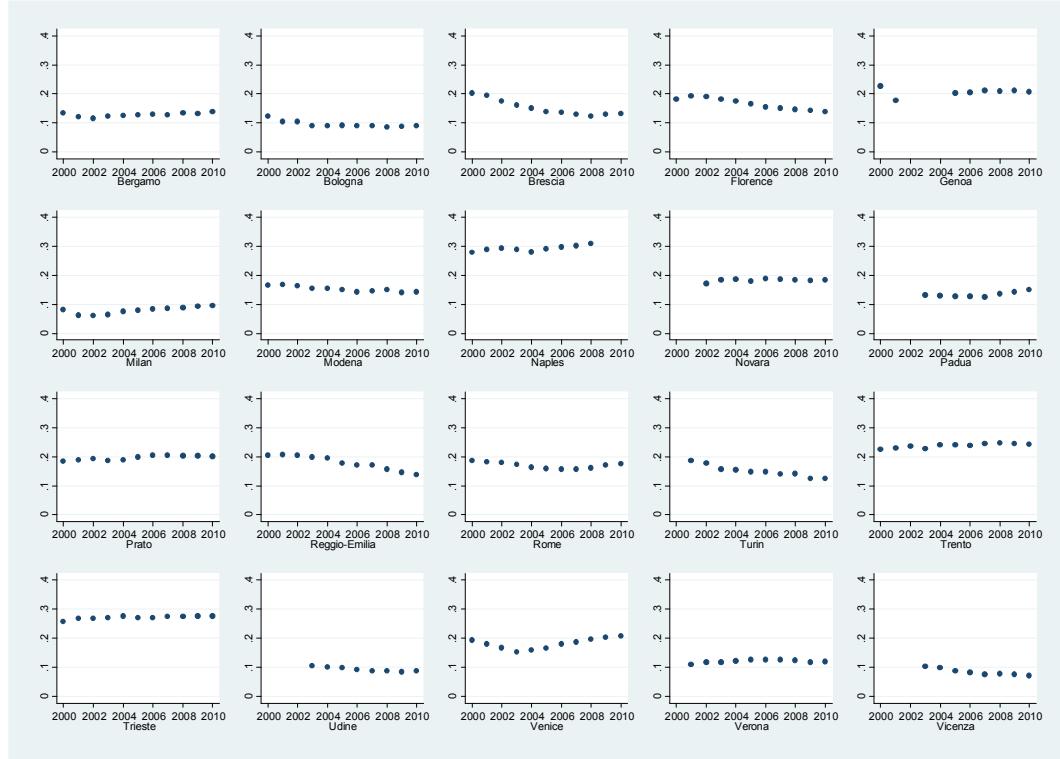
Table 9: Impact of immigration on city price distribution

| Dependent variable:<br>Log of house price | OLS                 |                                 |                                | IV                |                                 |                                |
|---|---------------------|---------------------------------|--------------------------------|-------------------|---------------------------------|--------------------------------|
|   | City average        | Least expensive<br>neighborhood | Most expensive<br>neighborhood | City average      | Least expensive<br>neighborhood | Most expensive<br>neighborhood |
| Log of immigrants                         | 0.050***<br>(0.013) | 0.054**<br>(0.014)              | 0.048***<br>(0.013)            | 0.336*<br>(0.058) | 0.270***<br>(0.063)             | 0.379**<br>(0.059)             |
| City fixed effects                        | YES                 | YES                             | YES                            | YES               | YES                             | YES                            |
| Year fixed effects                        | YES                 | YES                             | YES                            | YES               | YES                             | YES                            |
| First stage F-statistics                  | -                   | -                               | -                              | 134.2             | 134.2                           | 134.2                          |
| Number of observations:                   | 16,511              | 16,511                          | 16,511                         | 16,511            | 16,511                          | 16,511                         |

Data refer to all Italian cities with at least 5,000 inhabitants and partitioned in at least 2 AdT microzones. Heteroskedasticity-robust standard errors.

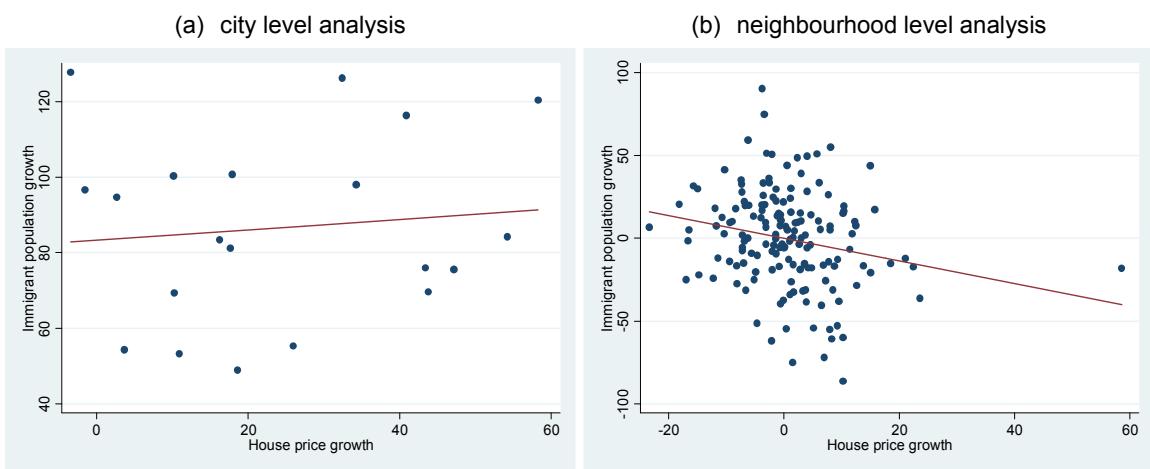
## Figures

**Figure 1: Spatial concentrations of immigrants in main Italian cities**



The dissimilarity index takes on a value of zero when each neighborhood contains a constant proportion of immigrants and a value of one when immigrants never share neighborhoods with natives.

**Figure 2: Immigrant population growth and house price growth in main Italian cities**



In panel (a) we plot the growth rate of immigrant population and of house price at the city level; in panel (b) the growth rates are computed at the neighbourhood level and as deviation from the city average. The growth rate is computed for the period 2003-2010 except that for Genoa (2005-2010), Modena (2005-2010), Naples (2003-2008), Novara (2005-2010), Padua (2005-2010), Rome (2004-2010), Turin (2004-2010), Trento (2004-2010), Udine (2004-2010), Venice (2005-2010) and Vicenza (2004-2010) because of data availability.