Immigration and Spatial Equilibrium: The Role of Expenditures in the Country of Origin

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Abstract

We document that international migrants concentrate more in expensive cities – the more so, the lower the prices in their origin countries are – and consume less locally than comparable natives. We rationalize this empirical evidence by introducing a quantitative spatial equilibrium model, in which a part of immigrants' income goes towards consumption in their origin countries. Using counterfactual simulations, we show that, due to this novel consumption channel, immigrants move economic activity toward expensive, high-productivity locations. This leads to a more efficient spatial allocation of labor and, as a result, increases the aggregate output and welfare of natives.

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1 Introduction

Prohibitively high housing costs in the most prosperous regions in the United States, such as the Bay Area or New York City, prevent many workers from moving to these locations and accessing their labor markets. In a recent paper, Hsieh and Moretti (2019) argue that the constrained housing supply in many of these large and highly productive metropolitan areas limits "the number of workers who have access to such high productivity," something that the authors refer to as the spatial misallocation of labor.

Despite their high cost and limited supply of housing, it is well-known that prosperous cities attract many foreign-born workers. Indeed, a closer look at the data reveals that there are large differences between natives and international migrants in terms of how likely they are to choose to locate in expensive, high-productivity cities. While 4.8% and 1.6% of natives lived in New York City and the Bay Area in 2019, respectively, these figures are 12.7% and 5.1% for international migrants. In this paper, we argue that, due to their different consumption patterns, immigrants have stronger incentives to locate in expensive and highly productive cities than natives, and we quantify how much immigration, through this consumption channel, contributes to reducing the spatial misallocation of labor.

We base our argument on the following idea. Immigrants tend to spend large fractions of their income in their home countries. Many send remittances to family members left behind, plan on returning, or simply spend their leisure time at home (Dustmann and Mestres 2010; Dustmann and Gorlach 2016). This means that they take into account not only the prices in the location where they live but also the prices in their home countries. We argue that, relative to natives, immigrants are less deterred by the high housing costs of the most productive cities because they consume less locally and consume more abroad. Hence, immigrants concentrate more in high-productivity cities, which helps to alleviate the spatial misallocation of labor identified in prior literature.

In the first part of the paper, we document three strong empirical regularities that support our argument. First, we show that immigrants concentrate disproportionately in metropolitan areas with high living costs, where, as it is well known in the urban economics literature, nominal wages and productivity tend to be higher (Combes and Gobillon 2014; Glaeser 2008). This fact also holds when we compare immigrants' and natives' location patterns within finely defined education, experience, and occupation groups. It is also robust to instrumenting local housing prices by exogenous determinants of housing costs, such as available land or estimates of the local housing supply elasticity, and when controlling for city size. Quantitatively, our results suggest that the *relative* probability of finding an immigrant is around eight times higher when local prices double.

Second, we show that there is a marked heterogeneity across immigrant groups. When home-country prices are lower, immigrants may prefer to consume a higher fraction of their income at origin. If so, this raises the incentives for immigrants from countries with low prices to locate in destinations with high prices. We use cross-origin and, arguably exogenous, within-origin variation in real exchange rates to document that when exchange rates are lower, immigrants' concentration in expensive cities is stronger. We also show, using Matricula Consular data on state-to-state migration flows from Mexico to the

United States, that Mexican immigrants from poorer states, where presumably price levels are lower, tend to disproportionately migrate to the richest and most expensive US states. All these results also hold when we flexibly control for both city and immigrant network size.

Third, we provide evidence that immigrant households consume around 15% less locally than comparable native households. Indeed, both when we use Consumer Expenditure Survey data and focus on local consumption or when we investigate housing consumption using Census and American Community Survey (ACS) data, we find that, conditional on being in the same city, immigrants spend less than natives with similar income levels, family sizes, and education. Immigrants tend to live in cheaper and smaller apartments, or, in brief, demand lower overall housing services than natives. We also document that these patterns are stronger for immigrants from countries with lower prices.

In the second part of the paper, we show how these empirical regularities can be readily explained by a standard spatial equilibrium model in which immigrants consume – for example, via remittances – a part of their income in the origin country. Intuitively, while in standard spatial equilibrium models a (marginal) native is indifferent between one location and an alternative one that is twice as expensive, as long as wages are also twice as high, immigrants' smaller share of local consumption implies that they prefer the high-wage, high-price city. As a consequence, immigrants concentrate in expensive cities, where they consume less housing and other non-tradable services, as we see in the data. Some degree of substitutability between home-country and destination goods makes this mechanism stronger for immigrants coming from cheaper countries, which is in line with the data on immigrant concentration both when we compare location patterns across countries of origin and when we relate them to fluctuations in exchange rates.

We argue that our mechanism, rather than alternative hypotheses, generates these patterns. The fact that the wages of immigrants relative to natives are lower in expensive cities – controlling for observable characteristics – suggests that these patterns are not driven by differential relative demands across cities. Complementarities among different types of workers are also unlikely to explain our results, since they also hold when we condition on particular education levels. Our results are also unlikely to be driven by immigrant networks. We perform several robustness tests, which suggest that while immigrant networks have power in explaining where immigrants locate, our mechanism retains strong empirical bite. We also incorporate the role of immigrant networks in our theoretical model, acting as an amenity shifter specific to the country of origin. More generally, as we argue in more detail below, potential alternative mechanisms have a hard time explaining the systematic relationship between immigrant concentration heterogeneity and home-country prices, and, at the same time, the consumption patterns that we document.

In the third part of the paper, we estimate the model by matching the distribution of immigrants relative to natives in 1990, using variation across metropolitan areas and across countries of origin conditional on the relative size of local immigrant networks. The estimation identifies two key parameters. First, our estimates imply that immigrants' expenditure share in the home country would be around 13% if destination and origin prices were equal. Second, we estimate an elasticity of substitution between consuming locally and in the origin of around 3. Thus, due to the substitution effect, immigrants increase their expenditure share in the home country when it becomes cheaper relative to the destination country. We validate our estimation by showing that the model fits the data well and does a good job at predicting two additional non-targeted moments: the variation in the consumption of housing across origins and the immigrant inflows and native population growth patterns across cities between 1990 and 2000 observed in the data.

Finally, we use our model to study the extent to which immigration alleviates the spatial misallocation of labor. For this, we compute the spatial distribution of economic activity that would prevail if immigrants' consumption behavior was identical to that of natives and compare it to the baseline equilibrium. This exercise suggests that aggregate output and welfare in 2000 were around 0.47% and 1.58% higher, respectively, thanks to immigration. These effects are slightly larger than artificially lowering the housing supply elasticities in New York City, San Francisco, and San Jose – the three cities that Hsieh and Moretti (2019) identify as the main culprits for the spatial misallocation of labor – to that of the median city. Moreover, we quantify the impact of immigrants' different preferences on the distribution of workers across cities. We find that some of the most productive cities are 20-30% larger than they would be without immigration.

Overall, this paper contributes to the literature in two ways. First, it provides a new theory for immigrants' location choices within host economies that is well supported by a large set of empirical facts – many of which have not been documented in previous research. Other existing theories of immigrants' location choices can at best explain a subset of these facts, but none is able to explain all of them in a unified and parsimonious framework. Second, we use our framework to better understand how immigration is shaping economic activity across locations and in general equilibrium, which typically escapes empirical accounts of immigration in the existing literature that mostly relies on difference-in-difference type of comparisons.

Related literature

There are fundamentally two theories explaining immigrants' location choices. First, it is well known that immigrants tend to move to cities or regions that are thriving. One implication of this fact is that immigrants may be particularly important for "greasing the wheels" of the labor market since they arbitrage away excess demand – which can occur in initially cheap or expensive cities – across locations. This is explored theoretically in Borjas (2001) and empirically in Cadena and Kovak (2016). Second, many authors emphasize that immigrants tend to move where previous immigrants have settled (Munshi 2003). Local immigrant communities help new immigrants find jobs and suitable neighborhoods for their stay in the host country. Our paper provides a new way of thinking about immigrant locations, which has not been explored before and receives considerable support in the data. Furthermore, we show the importance of our new mechanism for the aggregate economy.

Our work is also related to several other strands of the literature. The model that we propose is related to a large body of recent work on quantitative spatial equilibrium models, summarized in Redding and Rossi-Hansberg (2017). In this literature, only Burstein et al. (2020), Caliendo et al. (Forthcoming), Piyapromdee (2021), and Monras (2020) use spatial equilibrium models to study immigration. In these papers, immigrants are not characterized by how they consume. Rather, they are defined by differences in observable characteristics that may be important for labor market outcomes but that are silent on many of the empirical facts uncovered in our paper.

We take the view that immigrants are characterized by the fact that they have an extra good in their utility function, which can only be consumed in their country of origin. This extra good may represent remittances, future consumption, or income spent during periodical stays in the origin country. Only a relatively small number of papers have effectively seen immigration in this way. This is the case, for example, in studies of temporary and return migration. In most of this work, authors think of migration decisions as a way to accumulate human capital or savings for the eventual return to the home country (see a review of the literature in Dustmann and Gorlach (2016) and the recent paper by Adda et al. (Forthcoming)). This literature, however, has not studied the effects of immigration on the spatial equilibrium of the host economy.

Finally, some studies have investigated how changes in relative prices between host and destination country due to nominal exchange rate fluctuations affect immigrants' behavior in terms of the amount of remittances sent, their use in the home country, and how this affects immigrants' reservation wages (Yang 2006, 2008; Dustmann et al. 2021). The findings in these studies are in line with this paper. In contrast to these studies, it is worth emphasizing that we explore the role of nominal disparities in the host country rather than in the sending economy and that our approach takes into account the spatial distribution of economic activity within host economies.

In what follows, we first describe our data in Section 2. Section 3 provides empirical evidence. We introduce and estimate a quantitative spatial equilibrium model consistent with this empirical evidence in Section 4. In Section 5, we use our model to build counterfactuals that help us quantify how much immigration alleviates the spatial misallocation of labor. Section 6 concludes the paper.

2 Data

2.1 Census, ACS, CPS, and housing market measures

Our main data sources are the US Census for the years 1980, 1990, and 2000, and the American Community Survey 2009-2011 downloaded from IPUMS (Ruggles et al. 2016). We use information on the metropolitan statistical area (MSA) of residence of surveyed individuals, the wage they received in the preceding year, the number of weeks they usually worked in the preceding year, and their country of birth. We include all individuals aged between 18 and 65, excluding military personnel and persons living in group quarters. Further, we exclude the population living outside MSAs and in MSAs that are not identified across all years, whose boundaries are not consistent over time, or for which the housing supply elasticity from Saiz (2010) is not available. This leaves us with a total of 185 MSAs. We define as immigrants all individuals born outside the United States who were not US citizens at birth.

We also use data from the Census and ACS to compute local price indices. We thereby follow Moretti (2013) and apply his code to our sample including the pooled 2009-2011 ACS data. From this, we obtain a local price index for each of the MSAs, which is based on the variation in local housing costs.[1]

To explore whether our results hold for data collected more frequently, we rely on the Current Population Survey (CPS). In particular, we use the CPS March supplement to generate yearly cross-sectional data on individuals, including information on their demographic characteristics, labor market variables, and location of residence. Sample selection and variable definitions are the same as for the Census data. As information on the birthplace of respondents is only available after 1994, we only use CPS data for the period 1994-2011.

Finally, as a measure for the flexibility of housing markets to meet demand, we take the housing supply elasticities estimated by Saiz (2010). We use these elasticities as instruments to capture variation in local prices that is orthogonal to local shocks that drive prices by affecting demand. Further, we also consider as separate instruments the two main determinants of the elasticity: the land unavailable for development within 50 km of an MSA's central business district, also provided by Saiz (2010), and the Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko et al. (2008).

To give a sense of the characteristics of the MSAs in our sample, Table 1 reports the MSAs with the highest immigrant shares in the United States using data of 1990, together with some of the main variables used in the analysis. Many of the MSAs with high levels of immigration are also expensive and pay high wages, such as Los Angeles, New York City, or San Francisco. Moreover, these cities, together with some others in California (e.g. San Diego and Santa Barbara) and in the greater Miami area, are those with the lowest housing supply elasticities in the sample. However, there are also a few small and cheap cities with highly elastic housing supplies, which are mostly located in California or Texas close to the border between the United States and Mexico and known for their large Latin American immigrant communities. The most notable among these are McAllen, El Paso, and Brownsville in Texas.

2.2 Consumer Expenditure Survey

To document consumption patterns, we employ two different data sets. First, we use the Consumer Expenditure Survey (CEX), which is maintained by the Bureau of Labor Statistics and has been widely employed to document consumption behavior in the United States. It is a representative sample of US households and contains detailed information on consumption expenditure and household characteristics. Unfortunately, it contains no information on birthplace or citizen status, making it unfeasible to directly identify immigrants. Instead, we rely on one of the Hispanic categories that identifies households of Mexican origin in the years 2003-2015.[2] The data set contains around 30,000 households per year, of which around 7% are of Mexican origin.

[1]We use the version of Moretti's price index that is calculated as the weighted sum of local housing cost and the cost of non-housing consumption, which is assumed to be the same across areas. Local housing costs are measured as the average of the monthly cost of renting a two- or three-bedroom apartment in an MSA.

[2]Monras (2020) shows that the overlap between individuals identified as Hispanics of Mexican origin and Mexican-born individuals is around 85% in Census data. This gives us confidence that, by using the Hispanic variable in Consumption Expenditure data, we are capturing a large number of Mexican-born individuals.

We also document consumption patterns using the censuses and the ACS. Both record the rent paid by households who are renting. This is the most important local expenditure for many households and typically accounts for roughly 25% of (gross) household income.

2.3 World Bank data

An important aspect of our empirical analysis is to document the heterogeneity by price level of immigrants' origin country. To measure these, we use real exchange rate (RER) data, which are provided by the World Bank with respect to the United States for a large number of countries in its International Comparison Program database.[3] In Table E1 in online Appendix D, we provide a list of the top 10 and bottom 10 countries in terms of the average real exchange rate with respect to the United States across the years 1990, 2000, and 2010. While price levels in countries like Norway or Japan are around 35% higher, the number of countries with real exchange rates larger than 1 is relatively low. Australia, ranked 10th in the table, is only 7% more expensive than the United States. At the other end, countries like Vietnam (with large immigrant communities in the United States) have prices that are only 20% of those in the United States. Further, we use the bilateral Remittance Matrix provided by the World Bank for 2010, which is the earliest year available, to compute the total amount of remittances sent from immigrants in the United States to their origin countries.

2.4 Matricula Consular data

Mexican immigrants in the United States are encouraged to register in the local consulates, which issue a card called the Consular ID. In order to obtain this card, Mexican immigrants need to show their birth certificate or passport. In principle, both immigrants legally admitted to the United States and those that are undocumented can obtain this card. The card is useful, among other things, to open bank accounts in a number of financial institutions, which gives many Mexicans sufficient incentive to register. Among the information recorded with this registration process is the destination address in the United States and the municipality of origin within Mexico. These records allow to compute the bilateral flows of Mexicans in any given year. In theory, they can be computed at the municipality level, however, only state-to-state flows are publicly available. Caballero et al. (2018) and Allen et al. (2019) show that these data match well representative data sets on stocks. In this paper, we use the state-to-state migration flows for the year 2016.

3 Motivating facts

3.1 Immigrants concentrate in high local price index cities

In this section, we document the cross-sectional relationship between immigrant concentration and cities' price levels. We show that immigrants concentrate much more than natives in expensive cities, even when

[3]The data series is titled "Price level ratio of PPP conversion factor (GDP) to market exchange rate."

comparing natives and immigrants of similar characteristics. Our main hypothesis is that immigrants are more likely to choose these locations because part of their consumption is linked to their countries of origin, which gives them an advantage over natives for living in locations with high cost of living and high wages. We make this point explicit in Section 4. In what follows, we also provide evidence that should help to rule out potential alternative mechanisms such as immigrant composition, city size, reverse causality, and labor demand factors.

To document that immigrants concentrate more than natives in expensive cities, we define the *immigrant concentration* as the relative number of immigrants living in city c and regress this measure (in logs) on the price level of city c. As we show later, this regression is a reduced-form version of the relationship between the relative distribution of immigrants and city price levels implied by the model. More specifically, we run the following type of regression:

$$\ln\left(\frac{\text{Imm}_c}{\text{Imm}} / \frac{\text{Nat}_c}{\text{Nat}}\right) = \alpha + \beta \ln P_c + \varepsilon_c, \tag{3.1}$$

where Imm_c is the number of immigrants, Nat_c the number of natives, and P_c the corresponding price index in city c. Imm and Nat are the overall numbers of immigrants and natives in our sample, respectively. β measures how much more likely it is to find an immigrant in location c than a native. Hence, an estimate $\beta > 0$ implies that immigrants concentrate more in expensive MSAs than natives. Note that we can compute the *immigrant concentration* using the whole working-age population or restricting the computation to particular groups of workers – such as those with low or those with high education levels.

Results

In Figure 1, we first plot the immigrant concentration against the local price using data from the 1990 Census, where circle sizes indicate the size of the MSA in terms of working-age population. We find a strong positive relationship, implying that immigrants concentrate much more than natives in expensive metropolitan areas. The only notable outliers are three cities with very low prices but a high concentration of immigrants, which are the Texan cities located at the US border with Mexico mentioned above (Brownsville, McAllen, El Paso). Another outlier is Miami, the city with the largest immigrant concentration in the sample, which is well known for its large community of Cuban immigrants.

As a further step toward establishing that this is a strong feature of the data, we present a range of regression results in Table 2. Column 1 shows the pooled regression using the 1990 and 2000 Censuses and the 2010 ACS, with 185 different metropolitan areas and year fixed effects. The estimate in Column 1 is similar to the one displayed in Figure 1 using only 1990 data. In both cases, the point estimate is around 8, close to the labor supply elasticity estimated in prior literature (Diamond 2015), to which we return later.

In columns 2 to 4, we explore the sensitivity of this result to using different instruments for the local price index, which is potentially endogenous to housing demand changes induced by immigration. In

Column 2, we instrument the local price index using the Wharton Land Use Regulation Index. The point estimate is slightly larger and shows the same fact: immigrants concentrate in expensive locations. In Column 3, we use the share of land unavailable for development within a radius of 50 km from each MSA's central business district, while in Column 4 we use the Saiz (2010) estimates of the local housing supply elasticity (which are based both on regulations and unavailable land). The IV results suggest that the concentration of immigrants in expensive locations is not driven by reverse causality.

Columns 5 to 8 explore whether the results are driven by the fact that expensive cities also tend to be populous cities. Perhaps, immigrants have stronger preferences for locating in large metropolitan areas, for example because they offer amenities or products particularly attractive to immigrants (Albouy et al. 2018; Handbury Forthcoming) or because undocumented immigrants find it easier to evade deportation in locations with higher population density. Although population also has a significant positive effect on immigrant concentration in the OLS specification and reduces the effect of the price, the latter remains large and highly significant. Thus, controlling for population does not change the fact that immigrants strongly concentrate in expensive cities.

Robustness

We show a number of additional robustness checks in the Appendix, which we briefly discuss here. Figure A.1 shows the same type of graph as in Figure 1 for each census year using different measures of likely exogenous determinants of local prices, and controlling, in some of the graphs, for city size. It is clear from Figure A.1 that immigrants concentrate in expensive cities in each year of our sample and that this result does not depend on whether we condition on city size or on the measure of local prices that we use.

Table E2 shows that the results are unlikely to be driven by the different composition of immigrants and natives over observable characteristics. Using the same specification as in Column 8 of Table 2, Table E2 shows that immigrants concentrate in expensive metropolitan areas both when we include in the sample of immigrants either those that are likely documented or those that are likely undocumented, when we restrict the sample to four different education groups (high-school dropouts, high-school graduates, some college, and college graduates), when we remove immigrants from Latin American countries, when we restrict the sample to only young workers (aged 25 to 44), and when we restrict the sample to young workers for each of the four education groups.

Figure A.2 shows that we also obtain similar results when we condition on particular occupations. This figure plots a histogram of the estimates for 81 different occupations. All the estimates but two are positive and cluster around the mean estimate of 8.

Another potential concern is that immigrants might settle in more expensive cities because their labor markets are more dynamic and make it easier to find a job there. To address this argument, Figure A.3 shows that there is no systematic relationship between local price levels and job-finding rates or unemployment rates of immigrants. Thus, job opportunities for immigrants do not seem to be systematically better in expensive cities than in cheaper ones.

Finally, in Appendix A.1 we show in detail that our findings are unlikely to be driven by a higher demand for immigrant labor in more expensive metropolitan areas. When using the gap in composition-adjusted wages between natives and immigrants instead of the immigrant concentration as dependent variable, we find that this gap has a strong negative relationship with the city price level (see Table E4). Thus, relative to natives, immigrants earn less in more expensive cities, which is not consistent with a demand-driven explanation. This is also in line with evidence provided by Dustmann et al. (2021) who, using German data, find that a larger price gap between destination and origin is associated with lower wages of arriving immigrants. It is worth emphasizing that in Table E4 we adjust wages by observable characteristics and by the fact that immigrants and natives may be imperfect substitutes in production as we explain in detail in Appendix Section A.1.

3.2 Immigrant heterogeneity

In this section, we explore whether there is heterogeneity in how much immigrants concentrate in expensive locations. We use different data sets and sources of variation to show that immigrants who concentrate in expensive cities in the United States tend to be from countries of origin with low price indices, or, in other words, low real exchange rates with respect to the United States. This result holds both when comparing across countries of origin, within countries of origin using exchange rate variation over time, and when we compare immigrants from different regions within the same sending country. We also explore whether this heterogeneity can be explained by other factors, such as proxies for attachment to the United States. Some countries of origin see more migrants return, which may indicate lower attachment. Similarly, some immigrants send higher fractions of their incomes back to their country of origin. Finally, immigrants from certain countries of origin are more or less likely to be legally residing in the United States. We investigate this latter source of attachment to the United States using variation generated by the Immigration Reform and Control Act (IRCA) of 1986. Overall, price differences across countries seem to explain more systematically variation in immigrant concentration than heterogeneous attachment, a point we return to when discussing alternatives to our baseline model.

To visually explore the heterogeneity by country of origin, we start by estimating Equation (3.1) at the origin-city level (i.e. we replace Imm with the immigrant population from each origin). This allows us to estimate origin-specific coefficients β_o, which we can plot against the real exchange rate between the United States and the various countries of origin. More concretely, we use the reduced-form version of the specification shown in Column 6 in Table 2, but estimate the model origin by origin. That is, we account for potential scale effects by introducing as a control the total population in the metropolitan area and we address potential reverse causality by using directly the inverse of the housing supply elasticity instead of local prices.[4]

Panel A of Figure 2 plots this elasticity of the immigrant concentration for each country of origin (β_o), computed using Census and ACS data, against real exchange rates. Panel A shows a statistically

[4]The reason for why we use the reduced-form version of Column 6 of Table 2 rather than the IV specification is that we cannot compute local price indices at the yearly level with CPS data, which is the data used in Panel B of Figure 2.

significant relationship that goes in the expected direction. Immigrants from countries of origin with lower prices seem to concentrate more in cities with low housing supply elasticities.

Panel B of Figure 2 explores the same relationship focusing on Mexican immigrants only and exploiting the exchange rate variation at a yearly frequency using CPS data. Furthermore, given the higher frequency, we concentrate on Mexican movers, that is, individuals who change residence from year to year. Panel B of Figure 2 shows that, indeed, when the peso is lower relative to the dollar, Mexican immigrant movers are more likely to choose high-price locations, measured by the inverse of the housing supply elasticity.

Panel C of Figure 2 employs a third source of variation. Here, we use Matricula Consular data to explore how Mexican immigrants from various Mexican states of origin concentrate across states in the United States.[5] We proxy local prices with GDP per capita at the state level. Panel C of Figure 2 shows that Mexican immigrants from states of origin with low GDP per capita disproportionately migrate to US states with high GDP per capita.

To investigate the variation in real exchange rates across origins more systematically in a regression framework, we expand Equation (3.1) by calculating the dependent variable for each origin country, interacting the local price index with the real exchange rate and pooling the Census years 1990 and 2000 and the combined ACS data for 2009-2011 (real exchange rates are not available prior to 1990 from the World Bank). In particular, we estimate the following regression:

$$\ln\left(\frac{\text{Imm}_{c,o,t}}{\text{Imm}_{o,t}}/\frac{\text{Nat}_{c,t}}{\text{Nat}_t}\right) = \beta_1 \ln P_{c,t} + \beta_2 \ln RER_{o,t} + \beta_3 \ln P_{c,t} \times \ln RER_{o,t} + \beta_4 Net_{c,o,t} + \delta_t + \delta_o + \delta_c + \varepsilon_{c,o,t} \tag{3.2}$$

where, as before, $\ln P_{c,t}$ denotes the price level of city c, and $RER_{o,t}$ is the real exchange rate of origin country o with respect to the United States at time t. We estimate the relative share equation using a Poisson pseudo maximum likelihood (PPML) regression model in order to deal with the incidence of zeros (Santos Silva and Tenreyro 2006).[6] This further disaggregation also enables us to control for the presence of immigrant networks, a factor we have neglected thus far. Because the contemporaneous network, which we measure as the fraction of immigrants from origin o among the total city population at time t, is mechanically related to the immigrant concentration, we instead use the network predicted by the distribution of immigrants in the previous census year.[7] The estimate of interest is β_3. A negative estimate of β_3 indicates that immigrants from cheaper countries tend to concentrate more in expensive cities. It is worth noting that we measure all variables as deviations from their mean so that β_1 in this regression is comparable to the main estimate in Table 2.[8]

[5] Publicly available Matricula Consular data are provided at this level of geographic disaggregation.

[6] These results are based on the top 68 sending countries. In particular, we drop origin countries with fewer than 100 observations in any of the census years, small island countries, and Eastern European countries that did not exist before 1990. The resulting 68 origins account for around 90% of all immigrants in the sample.

[7] In particular, we allocate the total immigrant population from a certain origin according to its distribution across MSAs 10 years before and then divide this predicted immigrant stock by current city population (natives plus immigrants) to get the predicted network. Results are virtually identical when always allocating based on the 1980 distribution.

[8] β_2 captures the effect of the real exchange rate on the *average* concentration of immigrants from origin o at time t across

Results

Table 3 presents the results. The first column shows the simplest specification, where only the exchange rate, the local price index, and their interaction are included. The coefficient on the local price index is somewhat below 6. It indicates that, as we already documented in Table 2, immigrants concentrate in expensive cities more than natives. The interaction between the exchange rate and local prices is negative, which indicates that immigrants from countries with low prices concentrate even more in expensive metropolitan areas.

In column 2, we include as a control the size of the predicted local immigrant community. Immigrant networks have a strong positive correlation with immigrant concentration, however the inclusion of this control does not change the main estimates in column 1. Note that both column 1 and column 2 identify the parameters of interest from comparisons across countries of origin. In column 3, we include country of origin fixed effects. Hence, in this specification, identification comes from making within-country comparisons. In column 4, we also include metropolitan area fixed effects, hence removing any time-invariant characteristics of metropolitan areas that may be influencing immigrants' location choices, such as distance to the Mexico-US border. Estimates in both columns 3 and 4 lead to a similar conclusion. Immigrants seem to concentrate more in expensive cities when prices in the home country are lower. Columns 5 to 8 repeat the same specifications of columns 1 to 4 but include total population as a control, which leaves the results unchanged.

We show a number of robustness checks to these results in the Appendix. Table E5 explores the robustness of our results to introducing immigrant networks through different parametric and non-parametric specifications. Table E6 investigates the sensitivity of our results to flexibly controlling for population levels. Table E7 shows the results by groups of countries. All these tables confirm that our results are robust.

Taken together, the three graphs of Figure 2 and the results in Table 3 indicate that when home prices are lower, immigrants concentrate in high-price destinations even more strongly.

Additional evidence

While prices in the country of origin can explain in a systematic way the heterogeneity across immigrant groups, there may be other potential sources for heterogeneity. For instance, there may be heterogeneous preferences across immigrant groups. Perhaps some groups of immigrants are more attached than others to their home country. This would generate incentives for these immigrants to disproportionately concentrate in expensive cities at destination.

In this section, we expand the regressions shown in Table 3 by including three alternative sources of heterogeneity across countries of origin: variation in return migration rates, variation in the share of income remitted, and variation in the share of migrants who arrived before 1982, and, hence, who

cities. Note that, if immigrants are distributed exactly like natives, this average would be equal to 1 (or 0 when taking logs). However, as follows from our argument, immigrants tend to be more concentrated in expensive cities than natives and hence we expect $\beta_2 > 0$.

are more likely to be documented thanks to the Immigration Reform and Control Act (IRCA) of 1986 (which can be taken as an exogenous shock as we explain in more detail below).

First, we investigate whether immigrants from countries of origin with higher return migration rates are more likely to concentrate in high-price locations within the United States. For this, we use data from Azose and Raftery (2019), who estimate return migration rates for 67 of the origin countries in our sample.[9] Results are shown in columns 1 and 2. In column 1, we introduce the return migration rate and its interaction with local prices. If anything, it seems that migrants from countries with higher return migration rates are more likely to concentrate in high-price locations, although the effect is imprecisely estimated. The result is similar, and in this case marginally statistically significant, when we add prices in the origin country and their interaction with local prices at destination. Overall, this indicates that, conditional on the main mechanism highlighted in the previous section, higher attachment to the home country, proxied by higher return migration rates, induces immigrants to concentrate more in high-price locations.

Second, we explore as another proxy of home-country attachment the share of income remitted by immigrants. Computing this share for each origin is not an easy task. Individual-level data that contain both country of origin, income, and income remitted is hard to obtain.[10] Instead, we combine aggregate data based on the Bilateral Remittance Matrix provided by the World Bank, which reports total income remitted from the United States to each country of origin, with Census information on total income of immigrants in the United States. This allows us to construct a measure of the fraction of total income remitted by immigrants from each origin.[11] Using this information, which is only available starting in 2010, we investigate whether immigrants from countries with higher fractions of income remitted concentrate more in high-price locations. As can be seen in columns 3 and 4 of Table 4, we do not find much heterogeneity along this dimension, potentially due to the fact that we are measuring the share of income remitted with error.

Finally, we exploit variation generated by IRCA, which was a program that in 1987 gave all undocumented immigrants who arrived in the United States prior to 1982 the opportunity to apply for legal status. Hence, we can inspect whether the concentration of immigrants from different origins is related to the share of arrivals prior to 1982. For this, we focus on immigrant arrivals between 1978 and 1987, that is, a small band around the cut-off year of 1982. We use the immigrant concentration computed based on arrivals over this period as dependent variable, although the results expand to including immigrants arriving during any time period. The results are displayed in columns 5 and 6 of Table 4. As before, column 5 introduces the share of immigrant arrivals prior to 1982 interacted with local prices, while column 6 expands the regression to also include prices at origin and their interaction with prices at destination. The results indicate that immigrants from countries of origin with more pre-1982 arrivals, and, hence, those whose immigrant population is more likely to be documented and potentially more

[9] In particular, we match to each of the three years in our data Azose and Raftery (2019)'s estimates of the likelihood of a migrant returning from the United States to their origin country during the preceding five years.

[10] New Immigrant Survey data contain this information but only for 21 countries of origin with very small sample sizes – fewer than 50 individual-level observations for most countries of origin.

[11] `https://www.worldbank.org/en/topic/migrationremittancesdiasporaissues/brief/migration-remittances-data`.

attached to the United States, are less likely to concentrate in high-price locations at destination.

It is worth highlighting that no matter what source of additional heterogeneity by origin country we explore, the main results discussed in the previous sections remain unchanged. Immigrants, on average, concentrate more in high-price locations than natives, and this pattern is especially strong for immigrants from low-price origins. The theoretical model we introduce in Section 4 will replicate these patterns by allowing immigrants to substitute between local and origin consumption, whereby the exact expenditure shares depend on the ratio between origin and destination prices.[12]

3.3 Immigrants' consumption patterns

We argue that the previous results are at least partly driven by the fact that immigrants spend some of their income in their countries of origin. Related to this mechanism, Yang (2006) provides evidence that exchange rate fluctuations affect consumption in the origin countries using data for households in the Philippines and migrants in the United States. In particular, an appreciation of the US dollar leads to a higher probability of vehicle ownership and entrepreneurial income in households with members that currently reside in the US. Moreover, in line with this evidence, Yang (2008) shows that an appreciation of the dollar also increases remittances sent home by Filipino migrants.

Dustmann and Mestres (2010) report that immigrants in Germany remit around 10% of their income. While, as already mentioned, data of similar quality do not exist for the United States, we can compute the overall flow of outgoing remittances based on the data provided by the World Bank for selected years. In particular, we can compute the income remitted during the year 2010, which amounts to around \$110 billion. To obtain the total disposable income of immigrants residing in the United States, we sum up their total wage income and multiply it with the average US tax burden of around 32%, which results in \$540 billion. Thus, the remittance share of wage income is a very sizeable 20%.[13]

We now turn to the analysis of the local consumption of immigrants in the host economy relative to natives. As described in Attanasio and Pistaferri (2016), measuring consumption is not an easy task, with difficulties arising from measurement issues and from the treatment of durable goods. Our assumption is that total observed consumption can be decomposed into local consumption (part of which can be separately observed), savings, and remittances (or income spent in another country). Hence, if we find that immigrants spend less than natives locally (conditional on income), this must imply that they either save more (possibly to spend the savings after return to their home country), or spend a part of their income on remittances. This means that, by looking at local consumption, we can infer whether immigrants are likely to spend a part of their income in their countries of origin, as hypothesized.

More concretely, we employ two data sets to investigate whether immigrants consume less locally than natives: the Consumption Expenditure Survey (CEX) and the Census. The former allows us to

[12] As a robustness check, we also estimate a model where we allow for flexible heterogeneity across origins in the expenditures shares, meaning that the share of each origin is determined by a distinct parameter (details in Section 5.1). In Table E9, we regress these estimated parameters on exchange rates and find a strong negative correlation, lending further support to our proposed mechanism.

[13] Considering also non-wage income, the remittance share would be around 18%. For this exercise, we include all immigrants aged 18 to 65.

investigate overall consumption but only identifies Mexican immigrants. The latter allows us to identify immigrants from multiple countries of origin but contains only expenditures on housing, which represent around 25% of total expenditures (Davis and Ortalo-Magne 2011).

We start by analyzing the overall local consumption with CEX data using the following regression:

$$\ln \text{Total Expenditure}_{i,c,t} = \alpha + \beta \text{Mexican}_{i,c,t} + \sum_k \gamma_k \text{HH Income category } k_{i,c,t} + \eta X_{i,c,t} + \delta_c + \delta_t + \varepsilon_{i,c,t} \quad (3.3)$$

where the dependent variable is the quarterly total expenditure at the household level.[14] CEX data identify income only by category; hence, we use income bracket dummies indexed by k. *Mexican* is a dummy variable identifying households of Mexican origin, and δ_c and δ_t are location and time dummies, respectively. The coefficient of interest β measures the difference in total expenditures between Mexicans and non-Mexicans conditional on observable characteristics, most importantly income categories. $X_{i,s,t}$ is a vector of household characteristics that includes age, family size, race, and marital status. The location fixed effects (δ_c) ensure that the identification of β comes from within-location comparisons.[15]

Results

The results, reported in Panel A of Table 5, suggest that, unconditionally, Mexican households consume on average around 33% less than non-Mexican households, and as much as 38% when we force within-state comparisons (column 2). In column 3, we include income controls, which reduce the estimate to 15%. When we add all the household level controls in column 4, we find that Mexican households consume around 22% less locally than non-Mexican households. With close to zero savings rates (in the early 2000s the savings rate was around 2%), this number also represents the share of income that is potentially devoted to consumption in the home country and aligns well with the average income share of remittances.[16]

An important part of local expenditures are housing costs, for which we have information in both the CEX and Census data. In columns 5 to 8 of Panel A in Table 5, we repeat the regressions of columns 1 to 4 but use rent expenses as the dependent variable. The patterns are similar to those we observed in the first columns, showing that an important part of the difference between immigrants' and natives' consumption levels is likely driven by housing expenses. In particular, columns 7 and 8 suggest that Mexicans consume around 10% to 20% fewer "housing services" than comparable non-Mexicans.

To explore in more detail how immigrants and natives consume housing, in Panel B we turn to Census data, in which we can observe both ownership status and the rental expenses for renters. In Table E8 in the online Appendix, we show that immigrants are less likely to own the place where they live. Here, we concentrate on renters by running the same regression as in Equation (3.3) but using a continuous

[14] More specifically, we use the variable "totexpcq" from the CEX. This variable combines expenditures on all items.

[15] With CEX data, the lowest level of geographic disaggregation is the state.

[16] As can be seen in data from the St Louis Fed (`https://fred.stlouisfed.org/series/PSAVERT`), the aggregate personal savings rate has fluctuated between 2% and 12% since 1980. See also Dynan et al. (2004) for a discussion on how savings are lower for low-income households.

measure of income and MSA fixed effects.[17] When including these fixed effects in the second column of Panel B, we find that immigrant households spend around 14% less on rents than observationally similar natives, consistent with the results in Panel B. Controlling for household income shrinks the coefficient to a bit less than 10%.

In column 4, we restrict the sample to immigrant households and include the real exchange rate as a predictor to check whether immigrants from more expensive countries spend more on housing, conditional on income, household characteristics, and MSA fixed effects. Consistent with the model that we present in Section 4, immigrants from more expensive origins spend relatively more on housing in the host economy.

Columns 5 to 8 provide additional evidence that immigrant households consume fewer housing services than natives by using as dependent variable the number of bedrooms in the housing unit. Across specifications, we see that immigrant households live in housing units that have, on average, around .5 fewer rooms than units of comparable natives. We also observe variation across immigrant households from different countries of origin that is in line with the rent results.

Overall, these results suggest that immigrants spend less than natives on local goods and that immigrants coming from more expensive countries spend more income on housing, in particular space, in the host country, conditional on observable characteristics. We return to these results in Section 4.4 when we compare the heterogeneity in consumption patterns as a function of the real exchange rate predicted by the model and found in the data. The empirical patterns presented in this section will be an untargeted moment to test our model.

4 A spatial equilibrium model with immigration

In this section, we introduce a spatial equilibrium model that builds on Hsieh and Moretti (2019) with one important deviation: immigrants devote a part of their income to consume in their countries of origin. This model rationalizes the empirical evidence presented so far and allows to quantify how much immigration alleviates the spatial misallocation of labor.

4.1 Model setup

Utility and location choices

The utility of individual i from country of origin j in city/location c is given by:

$$\ln U_{ijc} = \rho + \ln Z_{jc} + (1-\beta)\ln C_T + \beta \frac{\sigma}{\sigma-1} \ln \left(\beta_l C_H^{\frac{\sigma-1}{\sigma}} + \beta_f C_F^{\frac{\sigma-1}{\sigma}} \right) + \ln \varepsilon_{ijc},$$

where $(1-\beta)$ denotes the expenditure share devoted to tradable goods C_T, and β_l and β_f denote the expenditure weights of local non-tradable goods C_H and foreign goods C_F, respectively. The elasticity

[17] Controls include a vector of individual characteristics, including dummies for the number of persons present in the household, sex, marital status, and age.

of substitution between local non-tradable and foreign goods is denoted by σ.[18] Z_{jc} denotes the utility derived from local amenities, which consist of a component Z_c that yields the same utility to both natives and immigrants independent of their origin, and a component Z_{jc}^{Net} that is specific to immigrants from origin j and represents, for example, the value derived from an existing network of immigrants from j in location c. Thus, $\ln Z_{jc} = \ln Z_c + \ln Z_{jc}^{Net}$. Finally, ε_{ijc} is a Frechét distributed idiosyncratic taste shock for living in location c and ρ is a constant ensuring that there is no constant term in the indirect utility function to be derived in what follows. Further, we assume $\beta_l + \beta_f = 1$ and denote natives by $j = N$.[19]

Note that C_H represents the consumption of housing and other non-tradable goods which need to be consumed in location c. For simplicity, we will henceforth refer to C_H as housing.

Individuals maximize their utility subject to a standard budget constraint, given by:

$$C_T + p_c C_H + p_j C_F \leq w_c,$$

where p_c is the price of housing and p_j is the price of foreign goods denominated in the home currency. The price of tradable goods is the numeraire and therefore equal to 1. The demand for each good is given by:

$$C_T = (1-\beta)w_c,\ \ C_H = \beta\beta_l \frac{w_c}{P_{jc}}(\frac{p_c}{P_{jc}})^{-\sigma},\ \ C_F = \beta\beta_f \frac{w_c}{P_{jc}}(\frac{p_c}{P_{jc}})^{-\sigma},$$

where

$$P_{jc}(\beta_l, \beta_f) = (\beta_l^{\sigma} p_c^{1-\sigma} + \beta_f^{\sigma} p_j^{1-\sigma})^{\frac{1}{1-\sigma}} \tag{4.1}$$

is the consumption price index for workers from origin country j. Note that this index varies across origins due to variation in origin price levels p_j if $\beta_f \neq 0$, and collapses to p_c if $\beta_f = 0$.

From this optimal demand functions, we obtain the following indirect utility of living in each location (derivation in Appendix B.1):

$$\ln V_{ijc} = \ln V_{jc} + \ln \varepsilon_{ijc} = \ln Z_{jc} + \ln w_c - \beta \ln P_{jc}(\beta_l, \beta_f) + \ln \varepsilon_{ijc}. \tag{4.2}$$

Note that V_{jc} captures the value of living in c for individuals from j, net of the idiosyncratic component.

Given this indirect utility, workers decide where to live by selecting the location that delivers the highest level of indirect utility given the realization of the taste shock. Denoting the inverse shape parameter of the distribution of ε_{ijc} by $\theta \geq 0$, which governs the variance of the idiosyncratic taste

[18] We opt for allowing only non-tradable goods to be substitutable with foreign goods for three main reasons. First, tradable goods to a large extent contain periodically purchased non-durable goods like food products that cannot be easily substituted with origin consumption. Second, due to their very nature, many durable tradable goods have similar prices across countries, which eliminates any motive for substitution. Third, the empirical evidence suggests that immigrants primarily save on housing expenses relative to natives. Allowing for a more flexible substitution across goods would yield similar insights as this model.

[19] There are alternative interpretations for what foreign consumption C_F represents. It could include consumption of non-tradables in the home country, remittances sent to relatives, or future consumption in the home country. Rather than attempting to model the specificities of each of these channels explicitly, we opt for a simple formulation that encapsulates all of them.

shocks, the outcome of this maximization yields:[20]

$$\pi_{jc} = \frac{V_{jc}^{\theta}}{\sum_k V_{jk}^{\theta}} = \left(\frac{V_{jc}}{V_j}\right)^{\theta}, \tag{4.3}$$

where π_{jc} denotes the share of workers from j that decide to live in city c, which depends on the indirect utility in location c relative to all other locations. In this equation, we define $V_j = (\sum_k V_{jk}^{\theta})^{\frac{1}{\theta}}$, which is the expected value, or, in short, welfare, of living in this economy for workers from country of origin j. We assume that each worker inelastically supplies one unit of labor to local firms, so that we can replace π_{jc} with L_{jc}/L_j, which is the share of labor supplied in city c by the workers from origin j. Using (4.2) and summing over j, we then obtain the overall labor supply in city c as

$$L_c = w_c^{\theta} \sum_j [(\frac{Z_{jc}}{P_{jc}^{\beta} V_j})^{\theta} L_j] = w_c^{\theta} L \sum_j [(\frac{Z_{jc}}{P_{jc}^{\beta} V_j})^{\theta} \frac{L_j}{L}]. \tag{4.4}$$

Equation (4.4) shows that the aggregate labor supply to a given location is increasing in wages and amenities and declining in housing costs. Both amenities and housing costs are origin specific, so that the aggregate labor supply in a city depends also on the composition of native and immigrant workers it can attract.

Production of tradable goods

Firms produce tradable goods with a production function that combines three inputs: labor, capital, and land for businesses. We assume perfectly competitive local labor markets. The productivity of firms varies at the local level, so that the total output of tradable goods produced in city c is given by

$$Y_c = A_c L_c^{\alpha} K_c^{\eta} (T_c^B)^{1-\alpha-\eta}, \tag{4.5}$$

where $L_c = \sum_j L_{jc} = \sum_j \pi_{jc} L_j$ is the sum of workers from all origins who live in c. Note that, to keep notation simple, we assume that natives and immigrants are perfect substitutes at the city level.[21] K_c denotes capital and T_c^B land for businesses. We assume that the cost of capital r is exogenously determined in world capital markets.

Profit maximization leads to the following demand for labor:

$$L_c = (\frac{\alpha^{1-\eta}\eta^{\eta}}{r^{\eta}} \frac{A_c}{w_c^{1-\eta}})^{\frac{1}{1-\alpha-\eta}} T_c^B. \tag{4.6}$$

As is standard in these models, Equation (4.6) implies that more productive locations and locations with more land available for businesses have a higher demand for labor.

[20] In principle, θ could be different for natives and immigrants. However, Amior (2020) provides evidence for assuming the same θ for both natives and immigrants. Nonetheless, we also explore implications of allowing for differences in θ between natives and immigrants.

[21] It is straightforward to introduce imperfect substitutability between natives and immigrants by assuming that $L_c = ((\sum_{j \neq N} L_{jc})^{\rho_I} + L_{Nc}^{\rho_I})^{1/\rho_I}$, where L_{Nc} indicates natives in location c. Introducing imperfect native-immigrant substitutability cannot explain the heterogeneity of the empirical patterns documented in Subsection 3.2 and would not yield any additional insights while complicating the algebra, which is why we abstract from it.

Housing market

The supply of housing services is provided by combining land for homes (T_c^H), which is a fixed factor and different from the land available for production, and a quantity Y_c^T of the final tradable good (Y) as inputs according to the following production function:

$$Y_c^H = H_c(Y_c^T, T_c^H) = \varsigma_c^{-\varsigma_c}(Y_c^T)^{\varsigma_c}(T_c^H)^{1-\varsigma_c}$$

where $1 - \varsigma_c$ is the weight of land in the production of housing. We assume land is owned by absentee landlords.[22]

From this, we obtain the following housing supply equation (derivation in online Appendix B.2):

$$Y_c^H = T_c^H(p_c)^{\gamma_c}, \tag{4.7}$$

where $\gamma_c = \frac{\varsigma_c}{1-\varsigma_c}$ is the housing supply elasticity. Note that when land has a higher weight in the production of housing, the elasticity of housing supply is lower.

Total demand for housing is given by the sum of the local demands of natives and immigrants, which are different as the latter also consume non-tradables in the country of origin. Local housing prices are implicitly defined by market clearing in each city:

$$T_c^H(p_c)^{\gamma_c} = [\beta\frac{w_c}{p_c}L_c][\frac{L_{Nc}}{L_c} + \sum_{j\neq N}\beta_l^{\sigma}(\frac{p_c}{P_{jc}})^{1-\sigma}\frac{L_{jc}}{L_c}] \tag{4.8}$$

Note that this equation reflects one of the differences between our model and standard spatial equilibrium models such as in Hsieh and Moretti (2019). With immigrants, the demand for housing in each location depends both on the size *and* the composition of the population. Without immigration, that is, when $\beta_f = 0$, we recover the standard equation $T_c^H(p_c)^{\gamma_c} = \beta\frac{w_c}{p_c}L_c$, which equates aggregate local supply of housing to aggregate local demand for housing. In this case, the housing market equilibrium delivers a simple (log) linear positive relation between housing prices and city population, which is what Hsieh and Moretti (2019) directly assume in a reduced-form way, that is, without explicitly deriving the housing supply and demand equations. In our case, it is necessary to explicitly model the housing market and derive a structural equation as it plays an important role in the counterfactual exercises that we conduct below. It also highlights one of the features of the data, namely that immigrants consume fewer housing services than natives, for example, by living in housing units with fewer bedrooms.

Equilibrium

Definition I. *The spatial equilibrium is defined as follows:*

1. *Workers decide where to live and how much to consume of each good.*

[22] A number of papers in this literature make this assumption. See, as an example, Eeckhout et al. (2014). Alternatively, the return on land, $r_cT_c^H$ – where r_c represents land prices – can be distributed to workers, who each hold a representative portfolio of the land in the economy.

2. Firms decide how many workers to hire to maximize profits.

3. Developers decide how much housing to supply.

4. Goods, labor, and housing markets clear.

4.2 Properties

Given these primitives, in this subsection we derive a number of properties, which are in line with the empirical evidence discussed so far. They are also the basis for the structural estimation described in Section 4.3, which allows us to quantify the effect of immigration on the aggregate economy.

Immigrant concentration

The difference between natives and immigrants is the weight they give to local and foreign price indices. We make this explicit with the following assumption.

Assumption. *Within the consumption of non-tradables, natives only care about local housing so that* $\beta_f = 0$ *and* $\beta_l = 1$*. Immigrants care about local housing and foreign-country goods, hence* $\beta_f > 0$ *and* $\beta_l + \beta_f = 1$*.*

With this definition of what, in the context of the model, being an immigrant means, we can use Equation (4.3) to obtain the following result.

Proposition 1. *The immigrant concentration is given by Equation 4.9, which is increasing in the local price level* p_c *and in immigrant-specific network amenities* Z_{jc}^{Net}*. It increases more steeply in* p_c *with lower origin prices* p_j*, iff* $\sigma > 1$*.*

$$\ln \frac{\pi_{jc}}{\pi_{Nc}} = \theta[\ln Z_{jc}^{Net} + \beta \ln \frac{p_c}{P_{jc}}] \tag{4.9}$$

Proof. Online Appendix B.3 □

Proposition 1 is directly linked to the facts that we report in Section 3. It shows that the concentration of immigrants is higher in expensive cities, especially so for immigrants from origins with lower prices p_j, as long as the substitution effect of a change in relative prices dominates the income effect. Proposition 1 also highlights that the immigrant concentration is higher in cities with amenities valued by immigrants, such as networks.

Equation (4.9) is also the basis for our structural estimation of the parameters θ, σ, and β_f. Note that the latter two parameters appear in the expression for P_{jc}, which is provided in Equation (4.1).

Immigration, total output, and misallocation

Following Hsieh and Moretti (2019), we solve the model in general equilibrium as a function of the local cost of living, which is defined as the local price index divided by the level of amenities. This is enough to illustrate the role that differences in the local cost of living across locations play in generating spatial misallocation and to show how immigration alleviates it.

For this, we start from Equation (4.3) to obtain a relationship between wages and aggregate welfare for workers from each country of origin:

$$\frac{L_{jc}}{L_j} = (\frac{V_{jc}}{V_j})^{\theta} \Rightarrow V_j = (\frac{Z_{jc}w_c}{P_{jc}^{\beta}})(\frac{L_j}{L_{jc}})^{\frac{1}{\theta}} \Rightarrow w_c = V_j(\frac{P_{jc}^{\beta}}{Z_{jc}})(\frac{L_{jc}}{L_j})^{\frac{1}{\theta}}.$$

Multiplying both sides by L_c and taking the sum over c we obtain

$$\sum_c w_c L_c = V_j \sum_c L_c(\frac{P_{jc}^{\beta}}{Z_{jc}})(\frac{L_{jc}}{L_j})^{\frac{1}{\theta}} = V_j L \sum_c \frac{L_c}{L}(\frac{P_{jc}^{\beta}}{Z_{jc}})(\frac{L_{jc}}{L_j})^{\frac{1}{\theta}}.$$

Rewriting the left-hand side as the labor share of output (i.e., using $\sum_c w_c L_c = \alpha Y$) and defining $Q_{jc} \equiv P_{jc}^{\beta}/Z_{jc}$ and $\bar{Q}_j \equiv (\sum_c Q_{jc}(\frac{L_{jc}}{L_j})^{\frac{1}{\theta}}\frac{L_c}{L})$ – which can be interpreted as the origin-specific cost of living and a weighted average of these costs across locations, respectively – we obtain the aggregate utility for workers from origin j as

$$V_j = \alpha\frac{Y/L}{\bar{Q}_j}. \tag{4.10}$$

Note that Equation (4.10) deflates output per capita by the average cost of living, which is specific to each country of origin, to translate output into units of utility.

To solve for aggregate output, and, hence, aggregate welfare, we need to combine the local labor demand and supply equations to obtain expressions for wages and employment as a function of the fundamentals – in this case local productivity and land in each location – and the costs of living.

Specifically, we first substitute V_j in (4.4) and solve for the wage:

$$L_c = w_c^{\theta} L[\sum_j(\frac{\bar{Q}_j}{Q_{jc}\alpha Y/L})^{\theta}\frac{L_j}{L}] \Rightarrow w_c = (\frac{L_c}{L})^{\frac{1}{\theta}}\alpha\frac{Y}{L}[\sum_j \frac{L_j}{L}(\frac{\bar{Q}_j}{Q_{jc}})^{\theta}]^{-\frac{1}{\theta}}.$$

We then substitute this expression into the labor demand (4.6), solve for L_c, and then aggregate labor across locations to finally solve for aggregate output:[23]

$$Y = (\frac{\eta}{r})^{\frac{\eta}{1-\eta}} L^{\frac{\alpha}{1-\eta}} \left((\sum_c \left(A_c(\sum_j s_j(\frac{\bar{Q}_j}{Q_{jc}})^{\theta})^{\frac{1}{\theta}})^{1-\eta}(T_c^B)^{1-\alpha-\eta} \right)^{\frac{1}{\psi}} \right)^{\frac{\psi}{1-\eta}} = AL^{\frac{\alpha}{1-\eta}} \tag{4.11}$$

with $\psi = (1-\eta)(1+1/\theta) - \alpha$, and $s_j = \frac{L_j}{L}$.

Intuitively, Equation (4.11) says that aggregate output can be written as aggregate labor, raised

[23] From:

$$L_c = \left((\frac{\eta}{r})^{\eta} A_c(\frac{Y}{L})^{\eta-1}(\frac{L_c}{L})^{\frac{\eta-1}{\theta}}(\sum_j \frac{L_j}{L}[(\frac{\bar{Q}_j}{Q_{jc}})^{\theta}])^{\frac{1-\eta}{\theta}} \right)^{\frac{1}{1-\alpha-\eta}} T_c^B$$

we obtain:

$$L = \sum_c L_c = \sum_c \left((\frac{\eta}{r})^{\eta} A_c(\frac{Y}{L})^{\eta-1}(\sum_j L_j(\frac{\bar{Q}_j}{Q_{jc}})^{\theta})^{\frac{1-\eta}{\theta}}(T_c^B)^{1-\alpha-\eta} \right)^{\frac{\theta}{\theta(1-\alpha-\eta)+(1-\eta)}}$$

to the weight of the local production function (once we endogenize the fact that capital is elastically supplied), and aggregate productivity A. In turn, aggregate productivity is a power mean of local productivities and land availability weighted by the inverse of the local cost of living relative to the average cost of living across all cities. In turn, the local and aggregate costs of living capture, through CES combinations, the heterogeneity in population that we have in the economy, which, in the case of our model, comes from the different preferences of natives and immigrants.

It is worth to compare Equation (4.11) to the one that would prevail without immigrants in the economy:

$$Y = (\frac{\eta}{r})^{\frac{\eta}{1-\eta}} L^{\frac{\alpha}{1-\eta}} \left(\sum_c \left(A_c (\frac{\bar{Q}_N}{Q_{Nc}})^{1-\eta} (T_c^B)^{1-\alpha-\eta} \right)^{\frac{1}{\psi}} \right)^{\frac{\psi}{1-\eta}}.$$

Without immigrants, the local cost of living depends exclusively on housing prices and local amenities. In our case, the local cost of living is a CES aggregate of the cost of living specific to natives and each immigrant group. In both cases, given that $(1-\eta)/\psi > 1$, these expressions show that a mean preserving spread or, in other words, a higher dispersion in the cost of living leads to lower aggregate output. This is the source of misallocation emphasized by Hsieh and Moretti (2019).

As seen by the expression for P_{jc}, the cost of living for immigrants is, in turn, a CES combination of local housing prices and foreign-country prices. Hence, across locations, the local cost of living has a common component – the foreign price index – and a component that is specific to each city: the price of housing. As a result, the cost of living of immigrants is less dispersed than that of natives, who only consume locally. Therefore, immigration reduces the dispersion in the local cost of living and contributes to alleviating the misallocation of labor induced by the dispersion in local housing cost.

Proposition 2. *When immigrants spend a part of their income on home-country goods, then an increase in the share of immigrants from any country of origin, holding total population constant, leads to an increase in aggregate output and welfare, since immigration reduces the spatial misallocation of labor.*

4.3 Estimation

We estimate the model by nonlinear least squares based on Equation (4.9). Conveniently, this equation gives us an expression for immigrant concentrations at the city-origin level without the need to determine the common amenity values Z_c and productivity levels A_c. We only need the origin-specific amenity levels and the local and origin prices to compute P_{jc}, which are a function of the parameters of interest β_f and σ.

More concretely, there are four key parameters in the model affecting the consumption and location choices of immigrants. β and β_f govern the share of income spent in the origin, while σ measures the sensitivity of this expenditure share to a change in the price ratio p_j/p_c.[24] Immigrants from origins with lower prices devote higher fractions of their income to home-country goods if $\sigma > 1$. Finally, θ governs

[24]Note that the origin expenditure share of an immigrant is exactly the product of β and β_f if $p_j/p_c = 1$.

the sensitivity of workers' location choices to differences in local fundamentals like wages or amenities. When idiosyncratic preference shocks have a low variance, the case of a high θ, workers are very sensitive to differences in utility levels across cities. In the extreme case of $\theta = \infty$, workers are perfectly mobile and utility levels are equalized across cities. In contrast, a lower value of θ indicates a higher attachment to specific locations for idiosyncratic reasons.

We base the estimation on the 1990 sample of 185 MSAs and 68 origin countries used in our empirical section. Local housing prices are measured as the rent component of the city-specific price index, computed following Moretti (2013), while origin prices are measured as real exchange rates. The immigrant concentration, computed as before, is the share of immigrants from origin j in city c among all immigrants from that origin divided by the share of natives in city c among all natives.

Immigrants' location choices are also shaped by the role of network amenities. To estimate the value of networks, we reduce the dimensionality by imposing the following structure on Z_{jc}^{Net}:

$$Z_{jc}^{Net} \equiv \exp(\phi \; Net_{jc} + \nu_{jc}),$$

where, as in Section 3.2, Net_{jc} is the predicted population share of immigrants from origin j in city c and ν_{jc} is an i.i.d. error term with zero mean. Thus, we assume that the log origin-specific amenity value is a linear function of the existing immigrant network plus an error capturing unobserved heterogeneity.

Since we cannot identify the share spent on tradable goods $1-\beta$ separately from the three remaining parameters stated above, we set the former equal to 0.4, which is the same as in Hsieh and Moretti (2019). With this assumption, we obtain the estimating equation

$$\ln \frac{\pi_{jc}}{\pi_{Nc}} = \theta[\phi Net_{jc} + 0.4 \ln \frac{p_c}{P_{jc}(\sigma, \beta_f)}] + \theta \nu_{jc}. \tag{4.12}$$

To derive a consistent estimator of $\lambda \equiv (\sigma, \beta_f, \theta, \phi)$, we impose the orthogonality condition $E[\nu_{jc}|p_c, P_{jc}, Net_{jc}] = 0$. Hence, the identifying assumption is that the unobserved residuals are strictly exogenous to prices and networks. Further, we need to introduce an additional restriction on the parameters because θ is not separately identified from the remaining three parameters. We can either set θ equal to a value taken from the literature or impose an additional constraint to be satisfied. We opt for the second option and show the robustness to fixing θ in Section 5. In particular, we set the economy-wide average of immigrants' expenditure share on origin goods equal to the remittance share of 20% that we identified in the data.[25] This uniquely pins down β_f as a function of σ.[26] Hence, we define the estimator as

$$\hat{\lambda} \equiv \arg\min_{\lambda} \quad \sum_j \sum_c [\nu_{jc}(\lambda)]^2 \quad \text{s.t.} \quad \frac{\sum_j \sum_c \omega_{jc} p_j C_{F,jc}}{\sum_j \sum_c \omega_{jc} w_c} = 0.2 \tag{4.13}$$

[25] We believe that this proxy is rather a lower bound for the actual share of expenditures on origin goods because it does not include savings or income spent during visits in the origin country.

[26] Note that if, for example, $\sigma = 1$ (the Cobb-Douglas case), β_f is equal to the (constant) origin expenditure share and thus the restrictions imply $\beta\beta_f = 0.2 \Rightarrow \beta_f = 0.5$.

where the weights ω_{jc} are the shares of immigrants from origin j living in city c in the total immigrant population across all cities.

Table 6 presents the values of the assumed and estimated parameters. With respect to the additional parameters that we need to solve the model, we follow Hsieh and Moretti (2019) and set the labor share $\alpha = 0.65$, the capital share $\eta = 0.25$, and the return to capital $r = 0.05$.

Our estimate of θ is 12.8, which is somewhat higher than other estimates in the literature (see Monras 2015; Caliendo et al. 2015). However, the comparison is not straightforward since the variation used in previous literature is quite different from the one used in this paper. The elasticity of substitution between local and origin goods σ is 3.18, β_f is 0.13, and ϕ is 1.30.

As a final step, we use the calibrated and estimated parameters as well as local wages from the data to compute local TFP, defined as the composite $A_c(T_c^B)^{1-\alpha-\eta}$, and the common amenity values Z_c implied by the model. We need these values for our counterfactual simulations in order to compute the full general equilibrium. We solve for TFP using Equation (4.6).[27] The values of Z_c can be obtained by removing the sum from 4.4, solving for Z_{jc} and setting $j = N$. Thus, we use the fact that $Z_{Nc} = Z_c$ and back out these parameters by matching the observed distribution of natives L_{Nc}/L_N in 1990 to the one predicted by the model given observed wages w_c and prices p_c.[28]

Further, when conducting counterfactual simulations, we make use of the housing market equations (4.7) and (4.8) to calculate the new equilibrium house prices resulting from changes in housing demand combined with the housing supply elasticities from Saiz (2010). For this, we compute the land used for housing T_c^H from Equation (4.8) given the parameters and the values observed in 1990 for native and immigrant populations, wages, and prices.

4.4 Comparison of the model versus the data

Goodness of fit

With the estimated parameters at hand, we can inspect the goodness of fit of the model by comparing the distribution of immigrants across cities predicted by the model with the data for 1990. For this, we compute the overall immigrant population shares (aggregated across origins) for each city and plot them against those observed in the Census data in Figure 3. Since, ultimately, we are interested in how the origin consumption channel built into our model affects overall TFP through shifting the distribution of population across cities, we sort MSAs by their productivity level along the x-axis.[29]

The model is able to replicate well both the general increase in the immigrant share with city-level productivity, driven by the higher price levels in more productive cities, and the considerably higher shares in the three cities at the border with Mexico, which we have already observed as outliers in Figure 1. In quantitative terms, the model is able to explain 74% of the variation in the immigrant

[27] Wages are measured as average residuals in city c in the year 1990 obtained from a Mincerian regression, as described in Section 2.1.

[28] Note that amenity values are not identified in absolute values because V_j is undetermined. However, only relative amenity values matter for the equilibrium, which is why we can set $V_j = 1$ and compute Z_c as $(p_c^\beta/w_c)(L_{Nc}/L_N)^{1/\theta}$.

[29] The city productivity levels used for this plot and the following are the logarithms of $A_c(T_c^B)^{1-\alpha-\eta}$.

share observed in the data. Note that the good fit of the model is to a large extent driven by the consumption channel, which makes immigrants, especially those from cheaper origins, more likely to choose high-price locations. If we shut down this channel by setting $\beta_f = 0$ for all immigrants, implying that they only differ from natives by valuing networks, the model is only able to explain 39% of the variation in the immigrant share in the data.

Non-targeted moments I: Heterogeneity in local expenditures by origin

Since immigrants spend a part of their income in their origin countries, more so if the real exchange rate is favorable, we can use the model to predict the expenditure on local non-tradable goods by origin. It is not straightforward to find a data equivalent for this expenditure, which is why we do not directly use it as a targeted variable in the model estimation. However, we can check whether the model predictions are consistent with the data by correlating them with the income share of rent expenses, which we already used in Section 3.3. To calculate these shares, we rely on rent expenditure from the Census, as the CEX data do not allow us to identify immigrants by origin. Specifically, we use the rent expenses divided by household income as the dependent variable in the same specification shown in Table 5, Panel B, column 3, replacing the immigrant dummy with origin-country fixed effects. We then plot the estimated fixed effects against the deviation of the share of local non-tradable expenditure from its average in the model in Figure 4. We find a tight significant relationship between data and model predictions.

Non-targeted moments II: Immigration over the 1990s

As a second check on non-targeted moments, we use the model to predict the change in the spatial distribution of natives and immigrants following the immigrant inflow that took place during the 1990s, the decade with the strongest increase in the total population share of immigrants in the United States since the mid-19th century.

To do so, we change the native and immigrant population levels (aggregated across cities) from their values in 1990 to those in 2000 and compare the equilibrium population distribution across cities implied by the model before and after the change. Thus, we predict city population growth driven by the channels present in our model, abstracting from potential changes in relative amenity values and productivity levels across cities in the 1990s. During this decade, the overall urban immigrant population in the sample increased from 10.7 million to 18.8 million, while the urban native population increased from 87.5 million to 98.9 million.[30] Thus, the total population share of immigrants rose from 12% to 19%. More than a third of this increase was due to inflows from Mexico, which amounted to around 3.35 million, followed by India with 0.45 million and Vietnam with 0.39 million.

In our simulations, house price changes depend on the increase in housing demand and the elasticity of housing supply in each city (see equations (4.7) and (4.8)). These price changes, together with the immigrant network and the origin consumption channel, will be key in driving city-specific population

[30] Note that these numbers only refer to individuals aged 18-65 living in one of the 185 MSAs included in the sample.

growth. In order to separately quantify the contributions of the different channels operating in the model, we conduct three counterfactual simulations. In the first one, there is no heterogeneity in consumption or amenities between natives and incoming immigrants (i.e., $\beta_f = \phi = 0$). In the second one, we introduce network amenities as the only difference in their preferences. Finally, in the third counterfactual, we simulate the full model with incoming immigrants deriving utility from network amenities and goods consumed in their origin countries purchased with local income.

Figure 5 shows for each city the immigrant and native population growth rates predicted by the three counterfactual simulations (panels A to C) and the actual growth rates observed between 1990 and 2000 in the data (Panel D). The rates are defined as the change in the respective population group (immigrants represented by blue dots, natives by red crosses) divided by the overall city population.

Panel A shows that, when natives and immigrants behave identically, there is relatively little variation in the inflow rates across cities for natives and almost no variation for immigrants. The variation in the inflow rates of natives across cities is purely driven by the heterogeneity in housing supply elasticities: natives locate disproportionately in cities with a higher elasticity. This is because, given that there is no change in productivity or amenity levels, those cities with more elastic housing supply experience smaller price increases as a result of a higher demand for housing and therefore become relatively more attractive. If housing supply elasticities were constant across cities, the native population growth rates predicted by the model would be constant and equal to the aggregate growth rate. As can be seen in the plot, the elasticity tends to be higher in less productive cities. Hence, low-productivity cities can attract relatively more native workers than more productive cities, which increases the spatial misallocation of labor and, therefore, reduces aggregate TFP. Note that, while the incoming migrants and the natives distribute across cities identically, the shape of their inflow rates is different due to the distinct location behavior of the immigrants already present in 1990.[31]

In Panel B, we simulate the model after introducing network amenities for immigrants. While the overall shape of the distributions of inflow rates remains almost identical, the model now predicts the border cities with very large Mexican communities and, to a smaller extent, Los Angeles to attract more immigrants.[32]

In Panel C of Figure 5, we finally simulate our baseline model incorporating both the network and origin consumption channels. Now, the distribution of the inflow rates looks drastically different. In particular, immigrant inflows increase with city productivity, with the exception of the predicted inflows above 20% for the border cities. At the same time, natives get “pushed out” of some of the cities at the high end of the productivity distribution, while their inflows into cities at the lower end of the distribution are larger. The cities that lose the most natives with respect to the simulation in Panel A are Los Angeles, San Francisco, and San Jose, which are the cities that experience the strongest house price increases due to their very inelastic housing supplies.

[31] In all simulations, we assume that the immigrants already present in 1990 behave as in the full model with network amenities and origin consumption in both counterfactuals. Thus, only the behavior of incoming immigrants differs between the simulations in panels A to C.

[32] In the three cities at the Mexico-US border, the share of Mexican immigrants among the working-age population (18-65) was around 24% in 1980.

Panel D plots the actual data of native and immigrant inflow rates. On the one hand, the model cannot replicate the large variation in these rates for low- and medium-productivity locations, which is also driven by local amenity and/or productivity shocks that we do not capture here. On the other hand, it is able to replicate the general pattern that immigrants disproportionately locate in high-productivity cities and those with large Mexican communities, while the opposite holds for natives. The model performs especially well in terms of the immigrant inflows in the most productive cities, predicting the largest inflow of almost 20% for San Jose, which is very close to the actual value. It also correctly predicts the lowest inflow rates among the group of high-productivity cities for Philadelphia and Detroit, whereas inflows are considerably over-predicted for Los Angeles, a city that is unique in both being highly productive and having a high amenity value for (primarily Latin American) immigrants due to networks.

In sum, Figure 5 suggests that the origin consumption channel goes a long way in explaining the observed patterns in immigrant and native population growth rates across US cities during the 1990s.

5 Immigration and Spatial Misallocation

Armed with the estimated model, we now use our framework to study the aggregate effects of the consumption and network channels of immigration on, first, output and welfare and, second, the population distribution.

5.1 Counterfactual analysis: Aggregate effects

As argued by Hsieh and Moretti (2019), high-productivity cities like New York City or San Francisco are more constrained with respect to the supply of housing. These constraints on housing lead to spatial misallocation: workers would be more productive in these locations, but they cannot afford the cost of living there. Our framework suggests that immigrants' distinct consumption preferences lead to a reduction in this labor misallocation, which we quantify in this section.

To do so, we conduct several counterfactual simulations, in which we vary the assumptions on immigrants' preferences. In particular, as a reference, we simulate the model under the assumption that natives' and immigrants' preferences are identical and compute the equilibrium aggregate output and native welfare prevailing in this counterfactual. We then compare these to the equilibrium output and welfare we obtain when simulating the baseline model with immigrants valuing network amenities and origin consumption.

In order to put the size of the effects of immigrants' heterogeneous preferences into perspective, we also calculate the output and welfare effects of relaxing some constraints on housing markets. Specifically, we first change the housing supply elasticities in New York City, San Francisco, and San Jose, which are the three most productive cities and also among those with the least elastic supplies, to the median elasticity across all cities. In a second counterfactual, we make the housing supply elasticity constant across all cities by setting it equal to the median everywhere. The upper panel of Table 7 shows the percentage changes in output and welfare for these two counterfactuals with respect to the baseline model. We obtain that changing the elasticity to the median in the three most productive cities alone increases output by 0.39%. Changing it to the median in all cities leads to an only somewhat larger increase of 0.49%. These output gains reflect the reduction in the spatial misallocation of labor due to the more elastic housing supplies in high-productivity cities, which leads to an expansion of the labor supply there. The welfare effects are considerably higher than the output effects as the former additionally reflect the decrease in the cost of living implied by less constrained housing markets. As constraints fall in a larger number of cities, the impact on welfare is obviously larger in the second counterfactual, which yields a 3.3% rise in welfare relative to the baseline.

The first row in the lower panel of Table 7 presents the effects of introducing preference heterogeneity between natives and immigrants in the model. The implied shift in the equilibrium distribution of workers across cities leads to an increase in output of 0.47%. Hence, this effect is of a similar size as the one obtained by setting housing supply elasticities to the median in all locations. As immigrants now shift consumption towards their origin and, hence, their demand for local housing is lower, they also reduce the pressure on house prices. As a consequence, we again find a larger effect on welfare than on output. The increase by 1.58% is around half of that of setting all housing supply elasticities to the median.

In the following two rows, we show the impact of introducing preference heterogeneity considering alternative parameterizations of the model. First, we assume that θ, the parameter governing the sensitivity of workers' location choices to dispersion in utilities across cities, is distinct for natives (θ_N) and immigrants (θ_I), and base their values on estimates provided by Diamond (2015).[33] In particular, we set $\theta_N = 5$ and $\theta_I = 7.8$, and then re-estimate the remaining parameters of the model.[34] Second, as an alternative to our estimated model with $\sigma > 1$ and one origin consumption weight β_f that is the same for all origins, we also consider an alternative, in which we set $\sigma = 1$. Hence, immigrants' consumption preferences are Cobb-Douglas and relative prices between their city of residence in the United States and their origin country do not affect expenditure shares. Instead, we generate the heterogeneity across origins observed in the data by estimating a different expenditure share $\beta_{f,j}$ for each origin. This alternative model that loads all the observed heterogeneity on preferences (conditional on immigrant networks) allows us to gain more confidence on our own baseline model. In Table E9, we regress the $\beta_{f,j}$ recovered from the spatial distribution of immigrants from each country of origin on exchange rates, networks, and other potential sources of immigrant heterogeneity. The table shows a strong correlation between these recovered parameters and exchange rate differences across countries of origin.

Looking at the output and welfare effects for each of these two alternatives, we find them to be only slightly smaller. In the first case, the lower effects can be naturally explained by the lower sensitivity of immigrants to spatial dispersion in utility levels implied by the lower value of θ_I relative to our baseline

[33] We use the values in Table 5 of Diamond (2015), who estimates a standard spatial equilibrium model (without endogenous amenities), albeit with two labor factor types. She argues that the labor supply elasticity of immigrants is higher than that of natives, however, the estimates for low-skilled immigrants are imprecise. Hence, we take the estimate for high-skilled immigrants, which has a higher precision. For natives, we take the round number which lays between the estimates reported in columns 1 and 2 of that table. Other estimates in the literature, such as as the ones provided by Notowidigdo (2020), point in the same direction. Using any of the alternative values does not significantly affect our results.

[34] We obtain the estimates $\sigma = 2.06$, $\beta_f = 0.15$ and $\phi = 2.01$. More generally, our main estimate and the ones obtained in robustness checks are consistent with the literature, see for example Shapiro (2006) and Albouy (2013).

estimate of 12.8. In the second case, we obtain smaller effects because higher relative prices in cities that attract more immigrants lead to a larger origin consumption share due to a dominating substitution effect in the baseline model with $\sigma > 1$. This reinforcement of the consumption channel is absent with constant expenditure shares under Cobb-Douglas preferences.

Lastly, we show what happens to output and welfare when assuming that immigrants value networks but, like natives, only consume local goods (i.e., $\beta_f = 0$). Since this leads to a larger concentration of immigrants in cities with relatively low productivity relative to the counterfactual with identical preferences (with the exception of Los Angeles, see Panel A of Figure 5), we now obtain a small negative output effect of 0.04%. The welfare effect for natives is slightly positive because the stronger concentration of immigrants in a few cities implies a (small) wage increase and lower pressure on house prices in the cities that are predominantly inhabited by natives.

Altogether, our framework highlights the importance of taking into account that immigrants spend a substantial fraction of their income in their countries of origin. The model-based counterfactuals presented in this section suggest that acknowledging this defining feature of immigrants adds to our understanding of how immigration affects the host economy.

5.2 Counterfactual analysis: Local effects

So far, we have focused on the aggregate output and welfare effects of immigrants' consumption preferences. In this final section, we investigate in more detail how these aggregate effects are generated by looking at the population effects induced by migrants' preferences at the local level. For this, we compute for each city the percentage difference in equilibrium population levels between the counterfactual with identical preferences of natives and immigrants and the baseline model.

Panel A of Figure 6 plots the percentage differences in overall population (pooling natives and immigrants) against the TFP level. As a result of the lower weight of immigrants' local expenditures, expensive cities with high TFP levels strongly gain in terms of size. San Jose and Los Angeles grow by 28% and 25%, respectively, while other highly productive cities like San Diego, Boston, Washington DC or New York City grow between 5% and 10%. Moreover, a range of less productive cities with large Mexican or Latin American communities in Texas and California grow around 10% thanks to their network amenities. In contrast, many other cities at the bottom of the TFP distribution lose up to 10% of their population.

Panel B plots the resulting changes in native population, which is close to a mirror image of the changes in overall population. This is because – due to the fixed factor in the production function: land – the marginal product of labor decreases with a higher amount of workers. This implies lower wages in those cities that grow more in terms of population. As a result, some natives relocate as these locations become less attractive. The cities with the highest TFP levels shrink by 5% to 15% in terms of native population, while cities on the Mexico–US border lose around 30% of their native populations.

In sum, these findings suggest that immigrants' distinct consumption preferences and valuation of networks have profound implications for the spatial distribution of workers across the United States.

There is strong population growth in expensive, high-wage locations while some natives are displaced and move to other locations. In turn, the stronger concentration of workers in these highly productive cities decreases spatial dispersion in nominal wages, which reduces the spatial misallocation of labor.

6 Conclusion

In the first part of this paper, we document that immigrants concentrate in more expensive cities relative to natives. We show that these patterns are stronger for immigrants coming from countries with low price levels and that immigrant households consume less locally than comparable native households.

We posit that these patterns emerge because a part of immigrants' income goes towards consumption in their countries of origin and, therefore, it is not affected by local prices but by the prices prevailing in their origin countries. That is, given that immigrants send remittances home or are more likely to spend time and consume there, they have a greater incentive than natives to live in expensive, high-productivity locations.

We build a spatial equilibrium model with distinct consumption preferences of natives and immigrants to assess the importance of this mechanism to explain the data and to quantify its impact on the economy. Using our estimated model, we show that the differential location choices of immigrants relative to natives have important aggregate implications as economic activity moves from low-productivity to high-productivity cities. Model simulations suggest that, through the consumption channel, immigration has increased output and native welfare by around 0.5% and 1.6%, respectively.

Regarding the size of the output effect of the consumption channel, there are two caveats to keep in mind. First, our model abstracts from city-level changes in TFP due to population changes. If productivity levels increase in locations with higher population growth (e.g., because of agglomeration forces), the output effects of immigration would accordingly be larger. Second, in our analysis, we abstract from rural areas, since Saiz (2010) does not provide estimates of housing supply elasticities for non-urban commuting zones. If immigrants are more concentrated in urban areas than in rural areas, which is likely to be the case given that the latter tend to be cheaper, less attractive to migrants in terms of networks, and less productive, this will have an additional positive effect on aggregate productivity not captured in our model.

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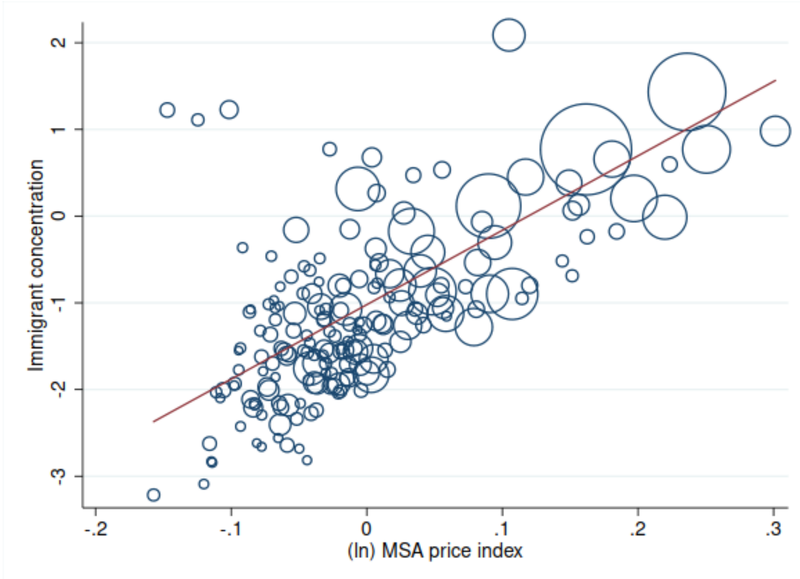
7 Figures

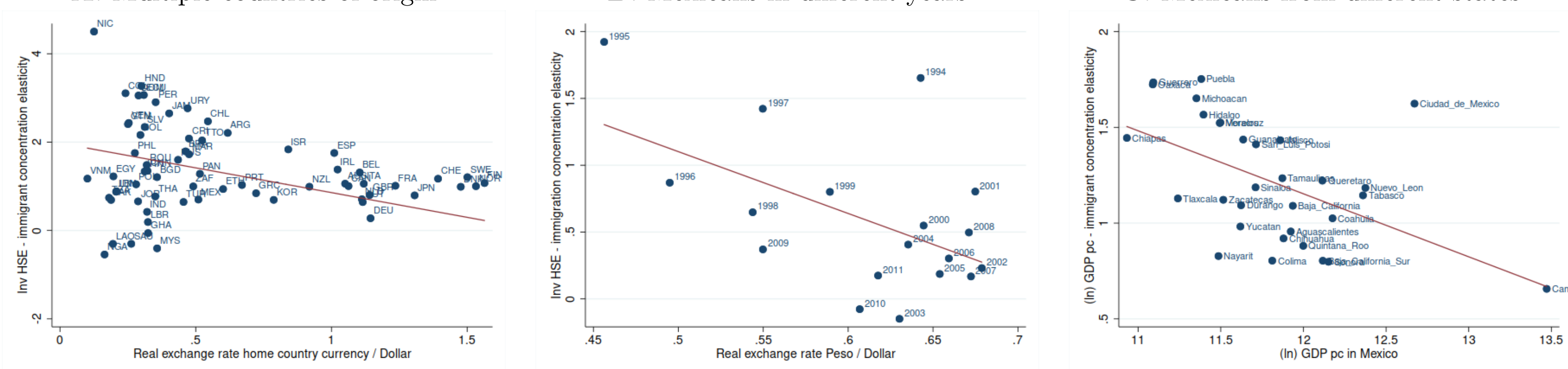
Figure 1: Immigration concentration



Notes: This figure shows the relationship between the immigrant concentration in a Metropolitan Statistical Area (MSA) and the MSA price index. Immigrant concentration is measured as the number of immigrants in the MSA relative to all immigrants in the United States divided by the number of natives in the MSA relative to all natives in the United States. Data are from the 1990 US Census.

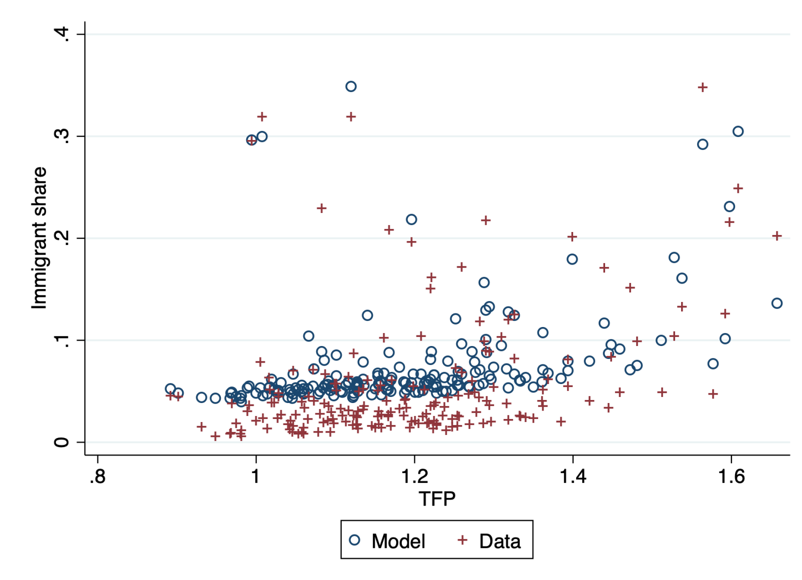
Figure 2: Heterogeneity in the city price elasticity of immigrant concentration

A. Multiple countries of origin **B.** Mexicans in different years **C.** Mexicans from different states



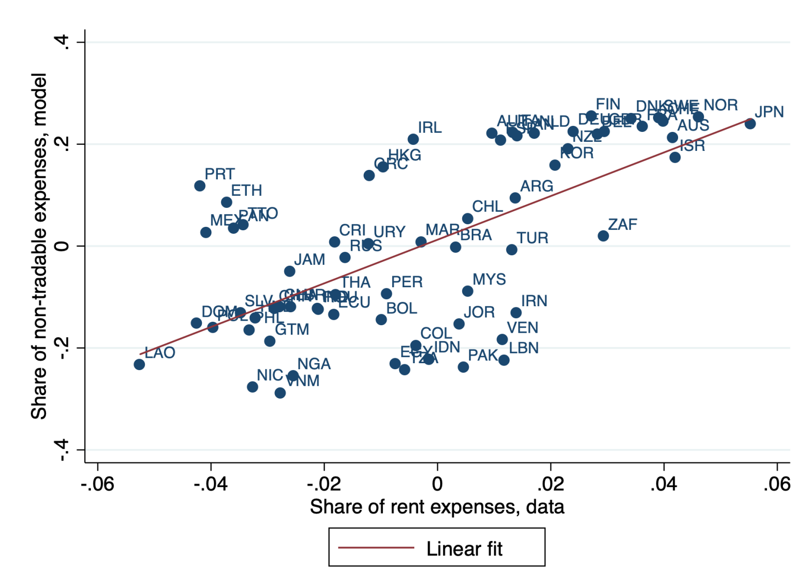
Notes: Based on Census and ACS data, Panel A plots the elasticity of the immigrant concentration with respect to the MSA inverse housing supply elasticity for each of the different countries of origin as a function of the real exchange rate. Based on CPS data, Panel B plots the elasticity of the Mexican concentration with respect to the MSA inverse housing supply elasticity for each year as a function of the Mexico-US real exchange rate. Panel C uses Matricula Consular data on migrant flows from Mexican states to US states to show the concentration of Mexicans across US states in terms of GDP per capita as a function of the GDP pc in the Mexican state of origin.

Figure 3: Model goodness of fit



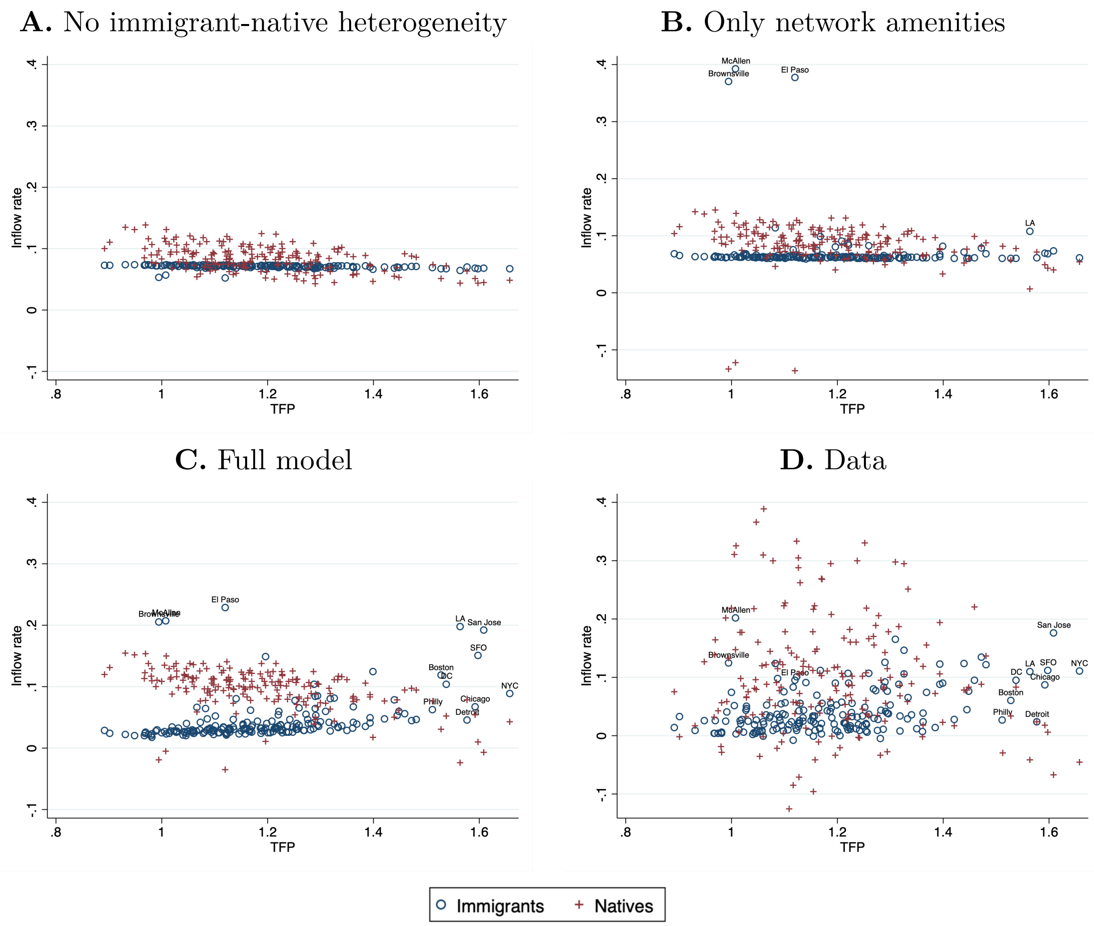
Notes: This figure compares immigrant shares predicted by the model and the immigrant share measured using data of individuals aged 18-65 from the 1990 Census. Each dot represents one MSA.

Figure 4: Non-targeted moments I: Share of expenditures on local non-tradable goods



Notes: This figure plots the income share of rent expenses in the Census data by country of origin (adjusted for income, family size, age, marital status, and travel time to work) against the share of expenditures in non-tradable goods predicted by the model (both as deviations from the mean).

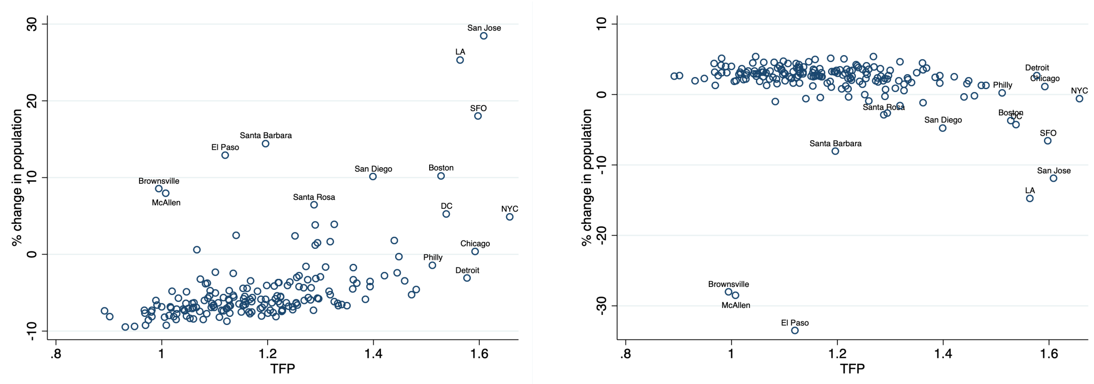
Figure 5: Non-targeted moments II: Model predictions and data of population changes from 1990 to 2000



Notes: This figure shows the 1990-2000 inflow rates of natives and immigrants in each MSA in the data and predicted by the model under different assumptions. Inflow rates are defined as changes in the MSA population of the respective group over total MSA population. Panel A shows the rates predicted by the model when natives and immigrants have identical preferences. Panel B shows the predicted rates when immigrants only differ from natives because they value networks. Panel C shows the predicted rates in the full model with immigrants valuing both home-country goods and networks. Panel D shows the data equivalents based on the sample of individuals aged 18-65 from the Census 1990 and 2000.

Figure 6: Contribution of immigrant-native heterogeneity to city population growth and wages

A. Population **B.** Native population



Notes: This figure shows the percentage change in overall and native population in each MSA predicted by our baseline model with respect to the predictions of the counterfactual in which immigrants and natives have identical preferences.

8 Tables

Table 1: List of top 20 US cities by immigrant share in the working-age population

MSA	Immig. (%)	Size rank	Population	Weekly wage	Price index	HS elasticity
Miami-Hialeah, FL	54	20	1,170,011	317	1.12	0.60
Los Angeles-Long Beach, CA	38	2	7,119,146	401	1.27	0.63
McAllen-Edinburg-Pharr-Mission, TX	33	99	202,608	242	0.87	3.68
El Paso, TX	33	68	330,378	277	0.91	2.35
Brownsville-Harlingen-San Benito, TX	30	124	137,397	243	0.89	2.40
San Jose, CA	28	24	978,436	462	1.36	0.76
New York, NY-Northeastern NJ	25	1	9,964,128	429	1.18	0.76
San Francisco-Oakland-Vallejo, CA	24	5	2,618,688	433	1.29	0.66
Visalia-Tulare-Porterville, CA	24	114	170,523	303	0.98	1.97
Fresno, CA	22	59	382,585	327	1.01	1.84
San Diego, CA	22	13	1,472,372	380	1.21	0.67
Santa Barbara-Santa Maria-Lompoc, CA	21	89	225,200	377	1.26	0.89
Stockton, CA	20	75	274,647	354	1.06	2.07
Modesto, CA	19	94	214,516	352	1.04	2.17
Riverside-San Bernardino, CA	18	14	1,467,227	379	1.13	0.94
Fort Lauderdale-Hollywood-Pompano Beach, FL	18	31	727,859	349	1.17	0.65
Houston-Brazoria, TX	17	10	2,147,484	377	1.00	2.30
Bakersfield, CA	16	72	303,741	358	1.01	1.64
Washington, DC/MD/VA	15	7	2,477,161	439	1.23	1.61
West Palm Beach-Boca Raton-Delray Beach, FL	14	47	474,321	357	1.18	0.83

Notes:: The population statistics are based on the sample of prime-age workers (18-64) from the 1990 Census. Weekly wages are computed by dividing yearly wage income of employees aged 25-59 by the number of weeks worked. Local price indices are computed following Moretti (2013). "HS elasticity" denotes housing supply elasticity, taken from Saiz (2010).

Table 2: Immigrant concentration and price levels

	Dep. Var.: Immigrant concentration							
	(1) OLS	(2) IV	(3) IV	(4) IV	(5) OLS	(6) IV	(7) IV	(8) IV
(ln) Price	7.803***	7.964***	8.752***	8.653***	5.781***	6.402***	8.184***	6.667***
	(0.721)	(1.275)	(1.465)	(0.866)	(0.799)	(2.164)	(2.115)	(1.836)
(ln) Population					0.225***	0.191	0.092	0.176
					(0.055)	(0.127)	(0.125)	(0.112)
Observations	555	555	555	555	555	555	555	555
R-squared	0.607	0.607	0.598	0.600	0.648	0.646	0.619	0.644
IV	. .	WRLURI	Unavailable Land	Elasticity	.	WRLURI	Unavailable Land	Elasticity
1st stage F-stat		40.47	29.24	60.27		33.53	28.22	27.38

Notes: The dependent variable is the immigrant concentration, which is measured as the number of immigrants in the MSA relative to all immigrants in the United States divided by the number of natives in the MSA relative to all natives in the United States. The regressions use Census and ACS data for 185 MSAs for the years 1990, 2000, and 2010. "WRLURI" indicates the Wharton Land Use Regulation Index, which is available for each MSA. "Unavailable Land" is the share of land unavailable for development within a radius of 50 km from each MSA's central business district. All the columns include year fixed effects. Observations are weighted by MSA population. Standard errors are clustered at the MSA level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 3: Immigrant concentration and price levels, heterogeneity by country of origin

	Dep. Var.: Immigrant concentration							
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML	(7) PPML	(8) PPML
(ln) RER	0.279***	0.125***	0.102*	0.079	0.286***	0.133***	0.102*	0.082
	(0.057)	(0.044)	(0.059)	(0.055)	(0.057)	(0.044)	(0.055)	(0.055)
(ln) Price	5.853***	5.094***	5.192***	1.730***	4.533***	4.131***	4.245***	1.668***
	(0.510)	(0.331)	(0.305)	(0.388)	(0.642)	(0.297)	(0.249)	(0.378)
(ln) Price × (ln) RER	-1.492***	-2.190***	-1.641***	-1.440***	-1.608***	-2.242***	-1.703***	-1.430***
	(0.490)	(0.463)	(0.383)	(0.352)	(0.542)	(0.490)	(0.419)	(0.349)
(ln) Population					0.224***	0.172***	0.167***	0.155
					(0.037)	(0.042)	(0.042)	(0.169)
Immigrant network		9.057***	10.497***	10.454***		8.817***	10.220***	10.456***
		(0.496)	(0.559)	(0.837)		(0.581)	(0.621)	(0.837)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	No	No	Yes	Yes	No	No	Yes	Yes
MSA FE	No	No	No	Yes	No	No	No	Yes
Observations	37740	37740	37740	37740	37740	37740	37740	37740
R-squared	0.075	0.085	0.1	0.232	0.095	0.101	0.113	0.232

Notes: This table shows regressions of the immigrant concentration on city prices, real exchange rates (RER), and their interaction. Data come from the Census and ACS and include 185 MSAs and 68 sending countries for the years 1990, 2000, and 2010. Standard errors are clustered at the MSA-origin level. Observations are weighted by the immigrant population in a year-MSA-origin cell. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 4: Immigrant concentration and price levels, alternative sources of country of origin heterogeneity

	Dep. Var.: Immigrant concentration					
	Return rates		Remittances		Pre 82 vs Post 82	
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
(ln) Price	4.153***	4.224***	3.622***	3.786***	4.598***	4.661***
	(0.284)	(0.238)	(0.612)	(0.538)	(0.260)	(0.232)
(ln) Return rate	0.083	0.062				
	(0.068)	(0.070)				
(ln) Price × (ln) Return rate	1.000	1.266*				
	(0.723)	(0.718)				
(ln) Price × (ln) Share Remitted			-0.224	-0.175		
			(0.181)	(0.174)		
(ln) Price × (ln) Share Pre-82 arrivals					-8.635***	-8.135***
					(1.879)	(1.629)
(ln) RER		0.128**		0.126**		0.037
		(0.059)		(0.059)		(0.071)
(ln) Price × (ln) RER		-1.844***		-1.897***		-1.690***
		(0.426)		(0.453)		(0.484)
(ln) Population	0.165***	0.166***	0.166***	0.167***	0.184***	0.186***
	(0.045)	(0.041)	(0.046)	(0.043)	(0.047)	(0.045)
Immigrant network	10.280***	10.214***	10.266***	10.200***	10.994***	10.943***
	(0.642)	(0.603)	(0.648)	(0.608)	(0.667)	(0.646)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37185	37185	35520	35520	37185	37185
R-squared	0.117	0.11	0.115	0.108	0.078	0.076

Notes: This table expands the regressions shown in Table 3 by including the (ln) return migration rate, the (ln) share of income remitted, and the (ln) share of immigrant arrivals pre-82, and their interaction with the (ln) MSA price index. Standard errors are clustered at the MSA-origin level. Observations are weighted by the immigrant population in a year-MSA-origin cell. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 5: Immigrants' expenditure

A.	(ln) Total Expenditure (CEX)				(ln) Rent (CEX)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mexican	-0.330***	-0.382***	-0.149***	-0.224***	-0.228***	-0.299***	-0.097***	-0.198***
	(0.028)	(0.021)	(0.012)	(0.014)	(0.060)	(0.025)	(0.023)	(0.019)
State FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Income	No	No	Yes	Yes	No	No	Yes	Yes
Characteristics	No	No	No	Yes	No	No	No	Yes
Observations	105975	105975	105975	105975	105975	105975	105975	105975
R-squared	0.031	0.063	0.301	0.314	0.018	0.079	0.226	0.249

B.	(ln) Rent (Census, ACS)				Number of Bedrooms (Census, ACS)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	-0.018	-0.143***	-0.073***		-0.602***	-0.491***	-0.407***	
	(0.024)	(0.023)	(0.018)		(0.057)	(0.044)	(0.032)	
(ln) RER				0.068***				0.139***
				(0.017)				(0.022)
(ln) HH income			0.277***	0.237***			0.329***	0.295***
			(0.004)	(0.005)			(0.022)	(0.022)
MSA FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	698277	698277	698277	149673	698277	698277	698277	149673
R-squared	0.295	0.443	0.539	0.513	0.240	0.264	0.299	0.223
Sample	All	All	All	Immigrants	All	All	All	Immigrants

Notes: Panel A uses data from the Consumer Expenditure Survey 2003-2015 with the log total expenditure and monthly rent expenses as dependent variables. The income controls added in columns 3 and 7 are dummies for household income bins. The characteristics added in columns 4 and 8 include age, race, family size, marital status, and a dummy indicating residence in an urban area. Panel B uses 1990 and 2000 Census and ACS 2009-2011 data for male household heads. Additional controls not shown include age, family size, and marital status. All specifications include year fixed effects. Standard errors are clustered at the state level in Panel A and at the MSA level in Panel B. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 6: Assumed and structurally estimated model parameters

Assumed parameters		Value	
Labor share in production	α	0.65	
Capital share in production	η	0.25	
Non-tradable goods spending share	β	0.40	
Return to capital	r	0.05	
Estimated parameters		Value	s.e.
Elasticity of substitution local-origin goods	σ	3.18	1.05
Share of home goods consumption	β_f	0.13	0.03
Sensitivity to local conditions	θ	12.8	5.53
Sensitivity to immigrant networks	ϕ	1.30	0.04

Notes: This table shows the structural parameters of the model estimated by nonlinear least squares using equation (4.12). For the estimation, we use data on the distribution of workers across locations at the country-of-origin level, local price levels, real exchange rates, immigrant networks, and the aggregate remittance share. Bootstrapped standard errors with 500 repetitions are reported.

Table 7: Changes in output and welfare relative to counterfactual without native-immigrant heterogeneity

	Output (% change)	Welfare (% change)
Effect of changing HS elasticity		
To median in NYC, SF, SJ	0.39	1.39
To median in all cities	0.49	3.32
Effect of native-immigrant heterogeneity		
Baseline model	0.47	1.58
Taking θ_N and θ_I from literature	0.31	1.49
With $\sigma = 1$ and origin-specific $\beta_{f,j}$	0.36	1.45
With network amenities only ($\beta_f = 0$)	-0.04	0.03

Notes: The upper panel shows the percentage changes in aggregate output and native welfare after setting the housing supply elasticities to the median in the indicated set of cities. The lower panel shows the respective percentage differences between the indicated counterfactual and the counterfactual simulation of the model with natives and immigrants having the same utility function.

FOR ONLINE PUBLICATION

A Empirical appendix

A.1 Evidence on Job-finding rates and wages

A potential explanation for why immigrants may concentrate in high-price metropolitan areas is that perhaps the demand for immigrant labor is higher in these locations. In this section, we argue that, based on employment and wage patterns observed in the data, demand factors are unlikely to be the main driver of our results.

Panel A of Figure A.3 plots the unemployment rates of immigrants, averaged from Current Population Survey (CPS) monthly data over the period 1995-2005, against city prices in the year 2000.[35] The relationship is flat, indicating that immigrants do not gain in terms of the probability of being employed in more expensive cities.

If the transition rates between employment and unemployment (i.e., both job-finding and separation rates) are higher in expensive cities, this might result in immigrant unemployment rates of similar magnitude. However, if immigrants care more about finding a job than about the job's duration (to establish an employment history, for instance), then they would still be drawn to larger cities. In Panel B, we therefore plot monthly immigrant job-finding rates instead of unemployment rates against city prices.[36] It shows a slightly negative relationship, suggesting that unemployment duration actually increases with the price level.

An alternative for detecting labor demand effects is to look at wages. In case of higher demand for immigrants in more expensive cities, we should either observe that their wages are relatively higher than those of natives, or, if mobility is perfect, that their wages are equal. However, when workers are heterogeneous and can be divided into different factor types, there are three potential issues.

First, it may be that immigrants and natives within narrowly defined skill groups are imperfect substitutes. Hence, even if their concentration is demand driven, they might earn less than natives, if the labor services usually offered by immigrants as opposed to natives pay lower wages. Second, the skill sorting of natives and immigrants across cities might be different and could partly drive local wage gaps. Third, it could be that the gap in earnings between natives

[35] As city prices are only available in 2000 or from 2005 onwards, we chose to average the CPS data during 11 years symmetrically around the year 2000 in order to get a sufficient number of observations of unemployed individuals per city. The results are robust to considering different time periods.

[36] The job-finding rate is calculated as the fraction of all unemployed individuals in a given month that is employed in the following month. In order to link individuals across months (whenever possible), we use the person identifier available from IPUMS.

and immigrants varies with education. For instance, it might be larger among high-skilled workers than among low-skilled workers. In this case, the higher concentration of high-skilled workers in larger cities (i.e the sorting of skills across cities) could generate higher average wage gaps in these locations.

To control for these factors, we combine the empirical approaches of Card (2009) and Ottaviano and Peri (2012). In particular, we estimate a model in which we relate the gap in wages between natives and immigrants to their relative labor supplies in a Metropolitan Statistical Area (MSA), following Card (2009). Moreover, we group workers in skill cells based on education and experience and calculate wage and employment ratios within those cells, as in Ottaviano and Peri (2012).[37] The inclusion of skill cell fixed effects absorbs any variation in wage gaps across cities due to different sorting along the education and experience dimensions. More concretely, we estimate the following regression:

$$\hat{w}_{I,k,c,t} - \hat{w}_{N,k,c,t} = \phi_k + \phi_{c,t} + \gamma \ln(\frac{L_{I,k,c,t}}{L_{N,k,c,t}}) + \varepsilon_{i,t}, \tag{A.1}$$

where $\hat{w}_{I,k,c,t}$ and $\hat{w}_{N,k,c,t}$ are the average composition-adjusted log wages and $L_{I,k,c,t}$ and $L_{N,k,c,t}$ the total hours worked in skill cell k and city c at time t for immigrants and natives, respectively. Since, compared to Ottaviano and Peri (2012), our data are further disaggregated at the MSA level, we opt for larger skill cells in order to have enough observations in each cell. In particular, cells are defined by two education groups (high school or less and at least some college) and four 10-year experience intervals.[38]

To account for the potential endogeneity problem that arises because the relative labor supply of immigrants might be driven by a higher relative demand for immigrant labor at the local level, we instrument their labor supply by the typical shift-share networks instrument. To do so, we allocate the national immigrant inflows to locations according to the distribution of the stock of immigrants from the same origin 10 years before. This strategy allows us to extract the city-time-specific component of the wage gaps as the city-time fixed effects $\phi_{c,t}$, which are adjusted for any effects due to spatial sorting or imperfect substitution between natives and immigrants within education-experience cells.

The last column of Table E3 in online Appendix D presents the estimate of the coefficient γ, which gives the negative inverse elasticity of substitution between natives and immigrants. For comparison, we show the estimates obtained with alternative specifications used in the

[37] Our main estimates use the mean of the composition-adjusted log wages as in Card (2009), although we replicate the original Ottaviano and Peri (2012) results and its sensitivity as discussed in Borjas et al. (2012).

[38] Results are robust to using the same cell definition as Ottaviano and Peri (2012).

literature in the first three columns.[39] In Column 4, we estimate regression (A.1) without MSA or MSA-year fixed effects. Thus, γ is identified using variation within skill cells over time and across MSAs. With this specification, we obtain a coefficient that implies an elasticity of substitution of around 20, which is the actual consensus estimate in the literature. However, after including MSA fixed effects in Column 5, the estimate becomes much smaller, implying an elasticity of 74. In our final specification with MSA-year fixed effects, the coefficient essentially becomes zero. Thus, once we account for MSA-specific time trends, we find no indication for imperfect substitutability between natives and immigrants at the local level (see also Borjas et al. 2012; Ruist 2013).[40]

In the next step, we relate these MSA-specific adjusted wage gaps, identified through $\hat{\phi}_{c,t}$, to the city price level using the following regression:

$$\hat{\phi}_{c,t} = \beta_P \ln P_{c,t} + \psi_c + \psi_t + \varepsilon_{c,t}. \tag{A.2}$$

An estimate of $\beta_P < 0$ indicates that the adjusted log difference in wages between immigrants and natives is greater (i.e. more negative) in more expensive cities.

We report the results of estimating Equation A.2 in Table E4, where we replicate the exact same format as Table 2 using this composition adjusted measure of wage gaps instead of the immigrant concentration. The results are a mirror image of Table 2: the gap in wages between natives and immigrants increases with the price level.

Taking all this evidence together suggests that demand effects are unlikely to be the main driver of immigrants' concentration in expensive cities.

A.2 Homeownership

If immigrants plan on returning to their countries of origin, it is likely that ownership rates are lower among them. Ownership rates vary considerably by income and other characteristics. Thus, it may be useful to see if it is indeed the case that homeownership rates are lower among immigrants than comparable natives. We investigate this with the following regression based on Census and ACS data:

[39] In the first column, we replicate the specification of Ottaviano and Peri (2012), which relies on national variation within skill cells across time (in particular, our sample selection and specification corresponds to *Pooled Men and Women* in Column 2 of table 2 in their paper. The fact that our coefficient is slightly lower might be driven by not including the year 1970 in our sample.) In Column 2, we follow Borjas et al. (2012) by using the mean of log wages instead of the log of mean wages as Ottaviano and Peri (2012). In column 3, we replicate the specification of Card (2009), Table 6, which relies on variation across the 124 largest MSAs in the year 2000 and uses composition adjusted log wages.

[40] This result is robust to only restricting the sample to large MSAs or alternately constructing the IV by allocating national inflows always based on the 1980 distribution of immigrants instead of using the preceding decade.

$$\text{Owner}_i = \alpha + \beta \text{Immigrant}_i + \gamma \ln \text{Household Income}_i + \eta_c X_i + \varepsilon_i \tag{A.3}$$

where "Owner" indicates whether the head of household i is a homeowner or not, Immigrant_i is a dummy indicating that household i has at least one immigrant, and X_i denotes various household characteristics, like the education level of the head of the household, marital status, the race of the head of the household, the size of the household, MSA fixed effects, occupation fixed effects, and time fixed effects. Thus, a negative β indicates that immigrants tend to rent rather than own the house in which they live, relative to comparable natives. The results are shown in Table E8. It is apparent that immigrants are around 10 percentage points less likely to own the house in which they reside.

B Theory appendix

B.1 Derivation of indirect utility

The utility in location c for an individual i from country of origin j can be written as:

$$\ln U_{ijc} = \rho + \ln Z_{jc} + (1-\beta)\ln C_T + \beta \frac{\sigma}{\sigma-1} \ln\left(\beta_l C_H^{\frac{\sigma-1}{\sigma}} + \beta_f C_F^{\frac{\sigma-1}{\sigma}}\right) + \ln \varepsilon_{ijc},$$

Individuals maximize their utility subject to a standard budget constraint, given by:

$$C_T + p_c C_H + p_j C_F \leq w_c,$$

We can solve this problem in two stages. For this, we need to define $E = p_c C_H + p_j C_F$, the expenditures on non-tradables. The first step is to allocate expenditures in non-tradables across the two non-tradable goods:

$$\max \beta \frac{\sigma}{\sigma-1} \ln\left(\beta_l C_H^{\frac{\sigma-1}{\sigma}} + \beta_f C_F^{\frac{\sigma-1}{\sigma}}\right) \quad \text{s.t.} \quad p_c C_H + p_j C_F = E$$

This leads to:

$$C_H = \left(\frac{\beta_l}{p_c}\right)^{\sigma} P_{jc}^{1-\sigma} E \tag{B.1}$$

$$C_F = \left(\frac{\beta_f}{p_j}\right)^{\sigma} P_{jc}^{1-\sigma} E \tag{B.2}$$

where:

$$P_{jc}(\beta_l, \beta_f) = (\beta_l^{\sigma} p_c^{1-\sigma} + \beta_f^{\sigma} p_j^{1-\sigma})^{\frac{1}{1-\sigma}} \tag{B.3}$$

The second step is to allocate spending between tradables and non-tradables. This is a maximization of a Cobb-Douglass utility function, so we obtain:

$$C_T = (1-\beta) w_c \tag{B.4}$$

$$E = \beta w_c \tag{B.5}$$

By substituting B.5 into B.1 and B.2, we obtain the final demand functions for C_H and C_F. Substituting these and C_T into into the direct utility function, we obtain the indirect utility function of the main text.

B.2 Derivation of housing supply equation

The supply of housing in city c is provided by combining land used for housing T_c^H, which is a fixed factor, and a quantity of the final tradable good Y_c^T as inputs according to the following production function:

$$\omega_c (Y_c^T)^{\varsigma_c} (T_c^H)^{1-\varsigma_c}$$

The housing supply equation is then derived from profit maximization as follows:

$$\max p_c \omega_c (Y_c^T)^{\varsigma_c} (T_c^H)^{1-\varsigma_c} - Y_c^T - r_c T_c^H$$

FOC w.r.t. Y^T:

$$p_c \omega_c \varsigma_c (Y_c^T)^{\varsigma_c - 1} (T_c^H)^{1-\varsigma_c} = 1$$

$$Y_c^T = (\varsigma_c \omega_c p_c)^{\frac{1}{1-\varsigma_c}} T_c^H$$

Now with this demand for tradables:

$$Y_c^H = \omega_c (Y_c^T)^{\varsigma_c} (T_c^H)^{1-\varsigma_c} = \omega_c ((\varsigma_c \omega_c p_c)^{\frac{1}{1-\varsigma_c}} T_c^H)^{\varsigma_c} (T_c^H)^{1-\varsigma_c} = \omega_c^{\frac{1}{1-\varsigma_c}} \varsigma_c^{\frac{\varsigma_c}{1-\varsigma_c}} (p_c)^{\frac{\varsigma_c}{1-\varsigma_c}} T_c^H$$

With $\omega_c = \varsigma_c^{-\varsigma_c}$, we obtain the expression in the main text.

B.3 Proofs of propositions of the quantitative model

Assumption. *Within the consumption of non-tradables, natives only care about local housing so that* $\beta_f = 0$ *and* $\beta_l = 1$. *Immigrants care about local housing and foreign-country goods, hence* $\beta_f > 0$ *and* $\beta_l + \beta_f = 1$.

With this definition of what, in the context of the model, being an immigrant means, we can use Equation (4.3) to obtain the following result.

Proposition 3. *The immigrant concentration is given by Equation 4.9, which is increasing in the local price level* p_c *and in immigrant-specific network amenities* Z_{jc}^{Net}. *It increases more steeply in* p_c *with lower origin prices* p_j, *iff* $\sigma > 1$.

$$\ln \frac{\pi_{jc}}{\pi_{Nc}} = \theta[\ln Z_{jc}^{Net} + \beta \ln \frac{p_c}{P_{jc}}]$$

Proof. We only need to use the labor supply equation for natives and immigrants of group j:

$$\frac{\pi_{jc}}{\pi_{jc}} = (\frac{V_{jc}}{V_c})^{\theta}$$

and substitute for the different terms:

$$\frac{\pi_{jc}}{\pi_{jc}} = (\frac{Z_{jc} w_c / P_{jc}^{\beta}}{Z_c w_c / p_c^{\beta}})^{\theta} = (Z_{jc}^{Net}(p_c/P_{jc})^{\beta})^{\theta}$$

Taking logs, we obtain the expression above.

To prove the first part of the proposition, we take the derivate with respect to p_c and multiply both sides by p_c:

$$\frac{\partial \ln \frac{\pi_{jc}}{\pi_{Nc}}}{\partial p_c} = \theta\beta(\frac{1}{p_c} - \frac{\beta_l^{\sigma} p_c^{-\sigma}}{\beta_l^{\sigma} p_c^{1-\sigma} + \beta_f^{\sigma} p_j^{1-\sigma}})$$

$$\frac{\partial \ln \frac{\pi_{jc}}{\pi_{Nc}}}{\partial p_c} p_c = \theta\beta(1 - \frac{\beta_l^{\sigma} p_c^{1-\sigma}}{\beta_l^{\sigma} p_c^{1-\sigma} + \beta_f^{\sigma} p_j^{1-\sigma}})$$

$$\frac{\partial \ln \frac{\pi_{jc}}{\pi_{Nc}}}{\partial p_c} p_c = \theta\beta \frac{\beta_f^{\sigma} p_j^{1-\sigma}}{\beta_l^{\sigma} p_c^{1-\sigma} + \beta_f^{\sigma} p_j^{1-\sigma}}$$

As $\partial \ln p_c / \partial p_c = 1/p_c$, the last expression is the wanted derivative, which is strictly positive:

$$\frac{\partial \ln \frac{\pi_{jc}}{\pi_{Nc}}}{\partial \ln p_c} > 0$$

To prove the second part of the proposition, we take the cross-derivative:

$$\frac{\partial^2 \ln \frac{\pi_{jc}}{\pi_{Nc}}}{\partial \ln p_c \partial p_j} = \theta\beta \frac{(\beta_l^\sigma p_c^{1-\sigma} + \beta_f^\sigma p_j^{1-\sigma})(1-\sigma)\beta_f^\sigma p_j^{-\sigma} - \beta_f^\sigma p_j^{1-\sigma}(1-\sigma)\beta_f^\sigma p_j^{-\sigma}}{(\beta_l^\sigma p_c^{1-\sigma} + \beta_f^\sigma p_j^{1-\sigma})^2}.$$

Multiplying both sides by p_j and again using $\partial \ln p_j / \partial p_j = 1/p_j$ we get

$$\frac{\partial^2 \ln \frac{\pi_{jc}}{\pi_{Nc}}}{\partial \ln p_c \partial \ln p_j} = \theta\beta(1-\sigma) \frac{\beta_f^\sigma p_j^{1-\sigma} \beta_l^\sigma p_c^{1-\sigma}}{(\beta_l^\sigma p_c^{1-\sigma} + \beta_f^\sigma p_j^{1-\sigma})^2} < 0 \quad \forall \sigma > 1$$

This concludes the proof.

□

C Figures appendix

Figure A.1: Immigration concentration, robustness

Panel A: Immigrant Concentration and MSA local price index

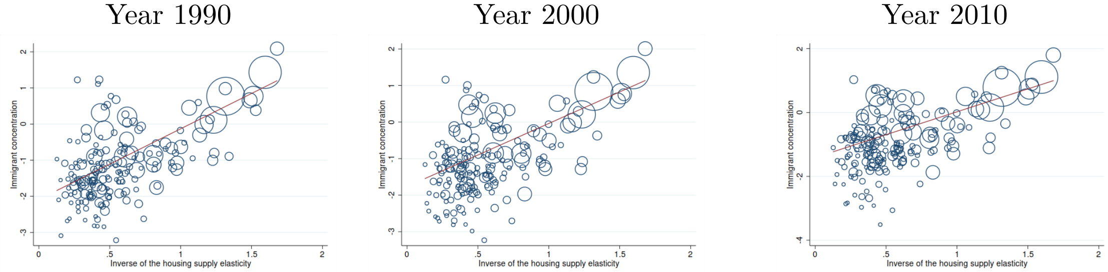
Year 1990 | Year 2000 | Year 2010

Panel B: Immigrant Concentration and MSA local price index, controlling for population

Year 1990 | Year 2000 | Year 2010

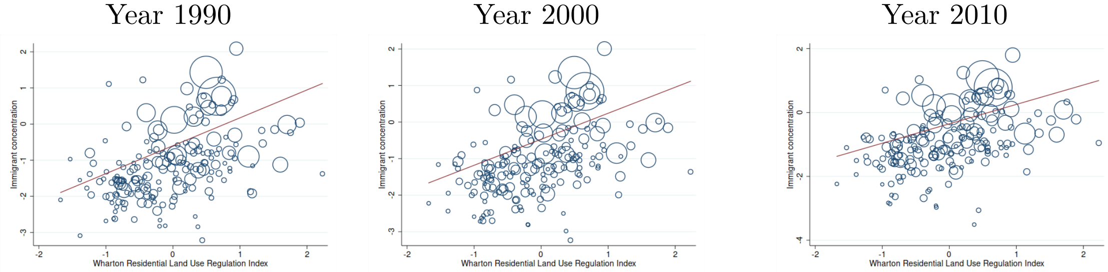
Panel C: Immigrant Concentration and inverse housing supply elasticity

Year 1990 | Year 2000 | Year 2010



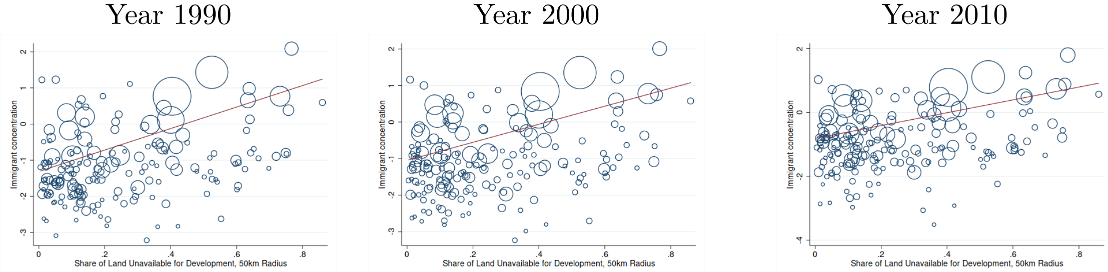
Panel D: Immigrant Concentration and Wharton Residential Land Use Regulation Index

Year 1990 | Year 2000 | Year 2010



Panel E: Immigrant Concentration and Share Land Unavailable for Development

Year 1990 | Year 2000 | Year 2010

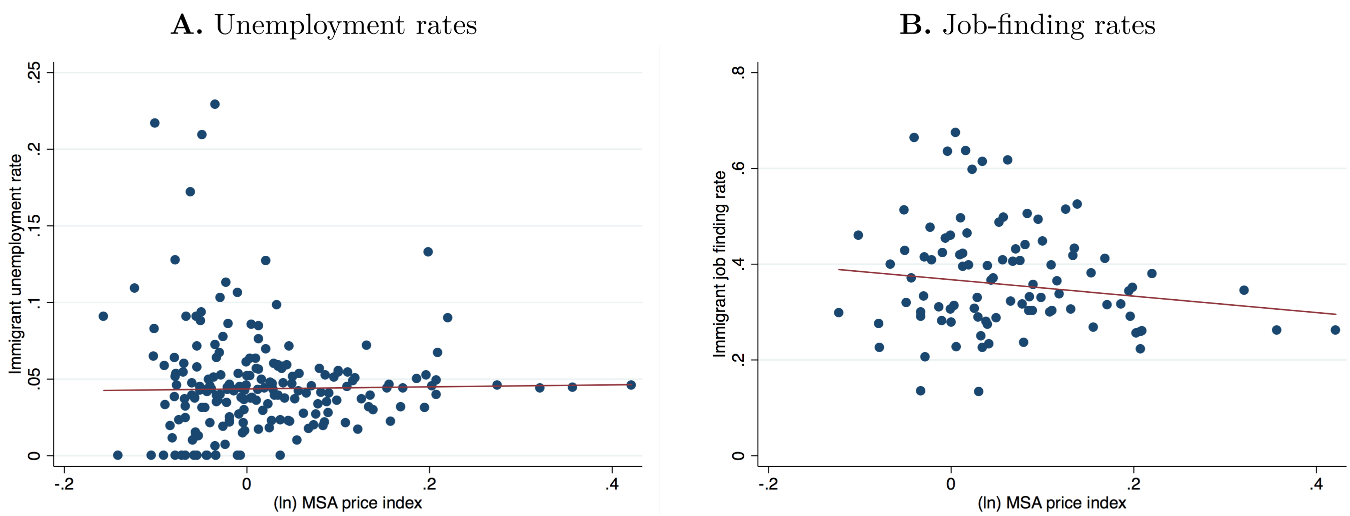


Notes: This figure shows the relationship between the immigrant concentration in a Metropolitan Statistical Area (MSA) and different measures of the MSA price index. Immigrant concentration is measured as the number of immigrants in the MSA relative to all immigrants in the United States divided by the number of natives in the MSA relative to all natives in the United States.

Figure A.2: Immigrant concentration - price index elasticity by occupation

Notes: This figure shows a histogram of the estimates of the elasticity of the immigrant concentration with respect to the MSA price index for 81 different aggregate occupations (which cover all the occupations recorded in Census data), controlling for population size and instrumenting the MSA price index with the Saiz (2010) estimates of the local housing supply elasticity. Data come from from the Census 1990 to 2000 and the combined ACS 2009-2011.

Figure A.3: City size, price index, and immigrants' unemployment and job-finding



Notes: This figure uses city price data from the 2000 Census and data for immigrant workers aged 25 to 59 from the CPS basic monthly files. The unemployment and job-finding rates are calculated for each city that can be matched to the Census data and are computed as the average of the variable over the period 1995-2005. The job-finding rate is the monthly share of unemployed job searchers transitioning to employment.

D Tables appendix

Table E1: Countries with the highest and the lowest real exchange rates

Highest		Lowest	
Norway	1.36	Vietnam	0.20
Japan	1.34	Pakistan	0.21
Bermuda	1.34	Yemen	0.23
Denmark	1.30	Egypt	0.24
Switzerland	1.29	Sierra Leone	0.24
Sweden	1.25	Sri Lanka	0.24
Finland	1.22	Nepal	0.25
United Kingdom	1.10	Indonesia	0.26
France	1.07	Tanzania	0.26
Australia	1.07	Nigeria	0.26

Notes: This table lists the top and bottom 10 countries with the highest and the lowest average real exchange rate over 1990, 2000 and 2010 with respect to the United States according to real exchange rate data from the World Bank.

Table E2: Immigration and city price levels, robustness

	A. Immigrant concentration, OLS											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(ln) Price	5.946***	6.334***	7.169***	7.503***	6.291***	4.524***	5.634***	5.819***	6.734***	7.585***	6.603***	4.529***
	(0.668)	(0.901)	(1.237)	(0.838)	(0.599)	(0.506)	(0.377)	(0.759)	(1.276)	(0.898)	(0.650)	(0.543)
(ln) Population	0.230***	0.318***	0.318***	0.248***	0.217***	0.207***	0.220***	0.259***	0.336***	0.272***	0.228***	0.201***
	(0.048)	(0.064)	(0.071)	(0.057)	(0.046)	(0.035)	(0.031)	(0.053)	(0.084)	(0.063)	(0.050)	(0.038)
Observations	740	739	739	740	740	740	740	740	737	738	739	739
R-squared	0.661	0.605	0.534	0.682	0.719	0.724	0.807	0.638	0.505	0.665	0.712	0.704
	B. Immigrant concentration, IV											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(ln) Price	9.287***	6.662***	10.750***	10.809***	8.777***	6.131***	7.856***	7.758***	8.711***	10.516***	9.120***	5.951***
	(1.876)	(2.091)	(3.237)	(2.085)	(1.539)	(1.228)	(0.870)	(1.916)	(3.093)	(2.201)	(1.637)	(1.237)
(ln) Population	0.075	0.303***	0.156	0.099	0.098	0.129*	0.117**	0.168*	0.243	0.141	0.108	0.133**
	(0.097)	(0.112)	(0.157)	(0.105)	(0.084)	(0.066)	(0.049)	(0.101)	(0.160)	(0.112)	(0.089)	(0.066)
Observations	740	739	739	740	740	740	740	740	737	738	739	739
R-squared	0.603	0.605	0.504	0.644	0.685	0.698	0.772	0.620	0.496	0.638	0.680	0.685
Sample	Docum.	Undocum.	<HS	HS	SC	C	No Lat. Am.	Young	Young + <HS	Young + HS	Young + SC	Young +C

Notes: This table shows regressions of the immigrant concentration on the city price index. City price indices are computed following Moretti (2013). Panel A presents OLS regressions, while panel B instruments the local price index by the housing supply elasticity estimated in Saiz (2010). Data come from the Census 1980 to 2000 and the combined 2009-2011 ACS data. Column 1 includes only documented immigrants. Column 2 includes only undocumented immigrants, who are identified following Borjas (2017). Column 3 restricts the sample to high-school dropouts. Column 4 restricts the sample to high-school graduates. Column 5 restricts the sample to workers with some college. Column 6 restricts the sample to workers with a college degree or more. Column 7 excludes immigrants from Latin American countries. Column 8 restricts the sample to young workers, aged below 45. Columns 9 to 12 repeat the exercises of Columns 3 to 6 but restrict the sample to younger workers. Robust standard errors clustered at the metropolitan area are reported. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table E3: Relative labor supply and the wage gap

	(1) OP	(2) BGH	(3) Card	(4) Eq. (A.1)	(5) Eq. (A.1)	(6) Eq. (A.1)
Rel. labor supply	-0.0355**	-0.0199	-0.0308***	-0.0529***	-0.0135**	-0.00571
	(0.0150)	(0.0150)	(0.00622)	(0.00398)	(0.00555)	(0.00712)
Observations	120	120	124	5,571	5,571	5,570
R-squared	0.791	0.763	0.809	0.287	0.391	0.473
Skill FE	yes	yes	no	yes	yes	yes
MSA FE	no	no	no	no	yes	yes
MSA-year FE	no	no	no	no	no	yes
F-stat 1st stage			696.9	1103	396.3	283.3

Notes: This table reports results of running regressions of relative immigrant wages on relative immigrant supplies based on data from the Census 1980 to 2000 and the combined ACS 2009-2011. Column 1 uses variation across experience, education groups, and decades (8 x 4 x 4, with 8 cells that are missing because of the experience definition based on age and years of education). In Column 1 we use the log of the mean of raw wages, as in Ottaviano and Peri (2012) (indicated by "OP"), to compute relative wages. Column 2 replicates the specification of Column 1, but we use as dependent variable the difference in the mean of the log of (raw) wages between natives and immigrants, as recommended in Borjas et al. (2012) (indicated by "BGH"). Column 3 uses variation across 124 metropolitan areas following Card (2009), Table 6, adjusting wages for composition. Columns 4 to 6 use variation across experience, education, metropolitan areas, and decade (4 x 2 x 212 x 4, with 1213 missing observations due to zero immigrants and (especially) lower coverage of metropolitan areas in 1970, which is used to build the IV for 1980). IV estimates are reported in columns 3 to 6 using the networks IV with the preceding decade immigrant distribution to assign flows. Robust standard errors clustered at the experience-education level (columns 1 and 2) and clustered at the metropolitan area (columns 3 to 6) are reported. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table E4: Immigrant-native wage gap and price levels

	Dep. Var.: (ln) Wage Gap							
	(1) OLS	(2) IV	(3) IV	(4) IV	(5) OLS	(6) IV	(7) IV	(8) IV
(ln) Price	-0.488***	-0.482***	-0.458***	-0.512***	-0.299***	-0.318**	-0.344***	-0.234**
	(0.073)	(0.086)	(0.113)	(0.079)	(0.080)	(0.126)	(0.125)	(0.111)
(ln) Population					-0.021***	-0.020**	-0.019***	-0.025***
					(0.005)	(0.008)	(0.007)	(0.007)
Observations	555	555	555	555	555	555	555	555
R-squared	0.409	0.409	0.407	0.408	0.466	0.466	0.464	0.463
IV	. .	WRLURI	Unavailable Land	Elasticity	.	WRLURI	Unavailable Land	Elasticity
1st stage F-stat		40.47	29.24	60.27		33.53	28.22	27.38

Notes: The dependent variable of this table is the immigrant-native wage gap, cleaned of observable characteristics and immigrant induced labor supply shocks. The table combines data of 185 MSAs for the years 1990, 2000, and 2010 Census/ACS. "WRLURI" indicates the Wharton Land Use Regulation Index, which is available for each MSA. "Unavailable Land" is the share of land unavailable for development within a radius of 50 km from each MSA's central business district. All columns include year fixed effects. Standard errors are clustered at the MSA level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table E5: Immigrant concentration and price levels, different network measures

	Dep. Var.: Immigrant concentration									
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML	(7) PPML	(8) PPML	(9) PPML	(10) PPML
(ln) RER	0.198***	0.272***	0.163***	0.497***	0.002	-0.028	0.100**	0.034	0.166***	0.090
	(0.044)	(0.062)	(0.043)	(0.066)	(0.043)	(0.039)	(0.040)	(0.041)	(0.054)	(0.063)
(ln) Price	4.272***	4.307***	4.405***	4.534***	2.516***	1.093***	2.724***	1.975***	3.024***	2.036***
	(0.348)	(0.339)	(0.265)	(0.227)	(0.613)	(0.341)	(0.630)	(0.515)	(0.710)	(0.741)
(ln) Price × (ln) RER	-2.076***	-1.772***	-1.897***	-1.464***	-1.575***	-0.841***	-1.783***	-1.436***	-1.589***	-1.329**
	(0.525)	(0.467)	(0.440)	(0.359)	(0.472)	(0.213)	(0.491)	(0.396)	(0.534)	(0.528)
(ln) Population	0.181***	0.180***	0.177***	0.174***	-0.221***	-0.696***	-0.159***	-0.395***	0.166***	0.121***
	(0.038)	(0.038)	(0.031)	(0.029)	(0.039)	(0.029)	(0.038)	(0.038)	(0.033)	(0.035)
Network, 1980	5.869***	6.204***								
	(0.617)	(0.651)								
Network, lagged			10.941***	12.386***						
			(0.483)	(0.669)						
ln(immigrant pop)					0.364***	0.752***				
					(0.032)	(0.028)				
ln(immigrant pop), 1980							0.302***	0.487***		
							(0.032)	(0.035)		
Network, group 2									0.195***	0.222***
									(0.054)	(0.047)
Network, group 3									0.282***	0.383***
									(0.053)	(0.049)
Network, group 4									0.324***	0.539***
									(0.053)	(0.055)
Network, group 5									0.437***	0.755***
									(0.055)	(0.059)
Network, group 6									0.525***	0.957***
									(0.054)	(0.064)
Network, group 7									0.624***	1.246***
									(0.055)	(0.074)
Network, group 8									0.752***	1.572***
									(0.052)	(0.086)
Network, group 9									0.939***	2.016***
									(0.053)	(0.096)
Network, group 10									1.879***	3.303***
									(0.122)	(0.148)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	37740	37740	37740	37740	37740	37740	37740	37740	37740	37740
R-squared	0.094	0.099	0.103	0.112	0.194	0.543	0.164	0.284	0.174	0.337

Notes: This table expands the regressions shown in Table 3 by including the different measures of immigrant network. Columns 1 and 2 compute immigrant networks from predicted immigrant populations based on 1980 data. Columns 3 and 4 include the same measure of immigrant networks but lagged one decade. Columns 5 and 6 use the size of the immigrant networks, rather than dividing it by the city population. Columns 7 and 8, use the predicted size of the immigrant network based on 1980 data. Columns 9 and 10 discretize our baseline measure of immigrant networks and introduced 10 different groups. The regressions are based on 185 MSAs and 68 sending countries from the 1990, 2000, and 2010 Census/ACS. Standard errors are clustered at the MSA-origin level. Observations are weighted by the immigrant population in a year-MSA-origin cell. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table E6: Immigrant concentration and price levels, different population measures

	Dep. Var.: Immigrant concentration							
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML	(7) PPML	(8) PPML
(ln) RER	0.131***	0.105*	0.083	0.128***	0.103**	0.083*	0.090	0.065
	(0.045)	(0.057)	(0.055)	(0.045)	(0.047)	(0.050)	(0.064)	(0.043)
(ln) Price	4.457***	4.557***	1.675***	4.139***	4.249***	1.916***	2.075***	0.919***
	(0.318)	(0.271)	(0.375)	(0.321)	(0.283)	(0.364)	(0.724)	(0.281)
(ln) Price × (ln) RER	-2.251***	-1.703***	-1.423***	-2.136***	-1.596***	-1.431***	-1.349**	-1.233***
	(0.477)	(0.405)	(0.347)	(0.457)	(0.381)	(0.348)	(0.529)	(0.321)
Immigrant network	9.005***	10.429***	10.472***	9.057***	10.508***	10.549***		
	(0.578)	(0.630)	(0.835)	(0.513)	(0.586)	(0.846)		
ln (native) Population	0.136***	0.133***	0.165					
	(0.044)	(0.044)	(0.150)					
(ln) Pop, group 2				0.382***	0.384***	0.347***	0.303***	0.325***
				(0.102)	(0.106)	(0.074)	(0.090)	(0.095)
(ln) Pop, group 3				0.409***	0.404***	0.330***	0.392***	0.341***
				(0.108)	(0.107)	(0.104)	(0.137)	(0.115)
(ln) Pop, group 4				0.322**	0.287*	0.252*	0.494***	0.330***
				(0.137)	(0.147)	(0.146)	(0.153)	(0.123)
(ln) Pop, group 5				0.478***	0.458***	0.402**	0.506***	0.249*
				(0.112)	(0.112)	(0.182)	(0.193)	(0.143)
(ln) Pop, group 6				0.434***	0.410***	0.255	0.523***	0.222
				(0.116)	(0.120)	(0.217)	(0.194)	(0.158)
(ln) Pop, group 7				0.592***	0.579***	0.383*	0.649***	0.263
				(0.113)	(0.112)	(0.217)	(0.180)	(0.189)
(ln) Pop, group 8				0.582***	0.577***	0.272	0.601***	0.367*
				(0.125)	(0.125)	(0.232)	(0.127)	(0.199)
(ln) Pop, group 9				0.890***	0.878***	0.536**	0.710***	0.434**
				(0.122)	(0.119)	(0.244)	(0.144)	(0.213)
(ln) Pop, group 10				0.850***	0.828***	0.387	0.721***	0.403*
				(0.125)	(0.119)	(0.271)	(0.166)	(0.230)
Network, group 2							0.162***	0.167***
							(0.047)	(0.047)
Network, group 3							0.330***	0.345***
							(0.045)	(0.048)
Network, group 4							0.498***	0.492***
							(0.051)	(0.051)
Network, group 5							0.721***	0.654***
							(0.056)	(0.053)
Network, group 6							0.929***	0.911***
							(0.061)	(0.058)
Network, group 7							1.221***	1.151***
							(0.070)	(0.061)
Network, group 8							1.557***	1.462***
							(0.083)	(0.068)
Network, group 9							2.006***	1.873***
							(0.092)	(0.076)
Network, group 10							3.307***	3.015***
							(0.144)	(0.097)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Metarea FE	No	No	Yes	No	No	Yes	No	Yes
Observations	37740	37740	37740	37740	37740	37740	37740	37740
R-squared	0.095	0.108	0.232	0.102	0.116	0.234	0.352	0.433

Notes: This table expands the regressions shown in Table 3 by including different measures of city size. In columns 1 and 2, we use the native population only. In columns 3 and 4, we discretize our baseline city size measure to create 10 different bins. In columns 5 and 6, we dicretize both city size and our measure of immigrant networks. The regressions are based on 185 MSAs and 68 sending countries from the 1990, 2000, and 2010 Census/ACS. Standard errors are clustered at the MSA-origin level. Observations are weighted by the immigrant population in a year-MSA-origin cell. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table E7: Immigrant concentration and price levels, different groups of countries

	Dep. Var.: Immigrant concentration								
	Europe			South America			Other countries		
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML	(7) PPML	(8) PPML	(9) PPML
(ln) RER	0.652***	0.088	-0.019	0.821***	-0.268	0.122	-0.059	0.148**	0.114*
	(0.081)	(0.134)	(0.168)	(0.180)	(0.186)	(0.115)	(0.062)	(0.070)	(0.061)
(ln) Price	5.581***	5.457***	1.725***	5.768***	5.714***	-1.455*	3.749***	3.870***	1.590***
	(0.462)	(0.448)	(0.470)	(0.462)	(0.438)	(0.814)	(0.281)	(0.264)	(0.429)
(ln) Price × (ln) RER	-1.641***	-1.466***	-1.517***	-1.482*	-1.502**	-2.867***	-2.700***	-2.286***	-1.674***
	(0.589)	(0.534)	(0.436)	(0.840)	(0.757)	(0.684)	(0.596)	(0.585)	(0.436)
(ln) Population	0.084***	0.084***	0.142	0.236***	0.236***	0.525**	0.163***	0.160***	-0.030
	(0.024)	(0.025)	(0.222)	(0.041)	(0.040)	(0.221)	(0.045)	(0.045)	(0.185)
Immigrant network	99.097***	108.502***	119.706***	81.705***	91.850***	27.816***	9.188***	10.062***	9.626***
	(5.778)	(7.102)	(15.083)	(7.290)	(8.748)	(6.983)	(0.490)	(0.554)	(0.811)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
MSA FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	9992	9992	9992	4995	4995	4995	22753	22753	22753
R-squared	0.001	0.001	0.001	0.001	0.001	0.003	0.087	0.107	0.204

Notes: This table expands the regressions shown in Table 3 by restricting the regression to particular groups of countries. The regressions are based on 185 MSAs and 68 sending countries from the 1990, 2000, and 2010 Census/ACS. Standard errors are clustered at the MSA-origin level. Observations are weighted by immigrant population in a year-MSA-origin cell. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table E8: Immigrants' homeownership rates

	(1) Ownership	(2) Ownership	(3) Ownership	(4) Ownership
Immigrant	-0.193***	-0.116***	-0.137***	
	(0.00937)	(0.00993)	(0.0178)	
(ln) HH income		0.213***	0.215***	0.231***
		(0.00411)	(0.00431)	(0.00686)
(ln) RER				-0.0135**
				(0.00573)
Observations	3,464,960	3,464,960	3,464,960	444,254
Year FE	yes	yes	yes	yes
MSA FE	yes	yes	no	yes
Sample	all	all	all	Imm. only

Notes: This table shows regressions with a dummy for home ownership as dependent variable using data from the 1990, 2000, and 2010 Census/ACS. Additional controls include dummies for the number of family members living in the household, marital status and age. Standard errors clustered at the MSA level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table E9: Immigrant heterogeneity correlates

	Dep. Var.: Home country implied expenditure share ($\beta_{f,j}$)					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
(ln) RER	-0.072***	-0.061***	-0.063***	-0.063***	-0.062***	-0.046***
	(0.020)	(0.018)	(0.017)	(0.017)	(0.018)	(0.016)
(ln) Immigrant network		-0.023***	-0.022***	-0.022***	-0.026***	-0.023***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
(ln) Return rate			-0.011	-0.011	0.003	-0.012
			(0.034)	(0.034)	(0.037)	(0.042)
(ln) Share Remitted					0.019	0.018
					(0.012)	(0.013)
Continent FE	No	No	No	No	No	Yes
Observations	68	68	67	67	64	64
R-squared	0.276	0.535	0.551	0.551	0.600	0.670

Notes: This table reports regressions of the implied share of home-country expenditures on country-level observables such as average real exchange rates, average immigrant network size, return migration rate, and share of income remitted. We estimate-home country expenditure shares from the relative distribution of immigrants from each country of origin across metropolitan areas assuming Cobb-Douglas utility functions instead of the utility function of our baseline model. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.