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

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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 toward 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. (*JEL* F24, J15, J31, J61, R23)

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, p.1) 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 percent and 1.6 percent of natives lived in New York City and the Bay Area in 2019, respectively, these figures are 12.7 percent and 5.1 percent for

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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. We also 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 percent less locally than comparable native households. Indeed, both when we use Consumer Expenditure Survey (CEX) 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 nontradable 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, and when we exclude occupations that prior literature has identified as complementing particularly well the high-skilled jobs that have been thriving in large cities (Autor and Dorn 2013). Our results are also unlikely to be driven by immigrant networks. We perform several robustness tests, which suggest that while immigrant networks have power to explain 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 percent if destination and origin prices were equal. Second, we estimate an elasticity of substitution between consuming locally and in the origin of around three. Thus, due to the substitution effect, immigrants increase their expenditure share in the home country when it is 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 nontargeted 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 0.46 percent and 1.59 percent 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 percent larger than they would be without immigration—again, similar in magnitude to the effect of lowering the housing supply elasticities in New York City, San Francisco, and San Jose to that of the median city.

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 rely on difference-in-difference types 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. (2021); 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, Dustmann, and Görlach (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, Ku, and Surovtseva 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 I. Section II provides empirical evidence. We introduce and estimate a quantitative spatial equilibrium model consistent with this empirical evidence in Section III. In Section IV, we use our model to build counterfactuals that help us quantify how much immigration alleviates the spatial misallocation of labor. Section V concludes the paper.

I. Data

A. *Census*, *ACS*, *CPS*, *and Housing Market Measures*

Our main data sources are the US census for the years 1980, 1990, and 2000, and the ACS 2009–2011 downloaded from IPUMS (Ruggles et al. 2022). 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 (2010a) 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 (2013a) and apply his code to our sample including the pooled 2009–2011 ACS data (Moretti 2013b). 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) from Flood et al. (2021). 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,

[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 nonhousing 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.

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 (2010a). 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 kilometers (km) of an MSA's central business district and the Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko, Saiz, and Summers (2008), all provided within the replication data provided by Saiz (2010b).

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 from 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.

B. *Consumer Expenditure Survey*

To document consumption patterns, we employ two different datasets. 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 (Bureau of Labor Statistics 2015). 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 dataset contains around 30,000 households per year, of which around 7 percent are of Mexican origin.

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

[2] Monras (2020) shows that the overlap between individuals identified as Hispanics of Mexican origin and Mexican-born individuals is around 85 percent 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.

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	329	1.12	0.60
Los Angeles-Long Beach, CA	38	2	7,119,146	416	1.27	0.63
McAllen-Edinburg-Pharr-Mission, TX	33	99	202,608	254	0.87	3.68
El Paso, TX	33	68	330,378	286	0.91	2.35
Brownsville-Harlingen-San Benito, TX	30	124	137,397	252	0.89	2.40
San Jose, CA	28	24	978,436	476	1.36	0.76
New York, NY-Northeastern, NJ	25	1	9,964,128	444	1.18	0.76
San Francisco-Oakland-Vallejo, CA	24	5	2,618,688	448	1.29	0.66
Visalia-Tulare-Porterville, CA	24	114	170,523	308	0.98	1.97
Fresno, CA	22	59	382,585	334	1.01	1.84
San Diego, CA	22	13	1,472,372	392	1.21	0.67
Santa Barbara-Santa Maria-Lompoc, CA	21	89	225,200	388	1.26	0.89
Stockton, CA	20	75	274,647	362	1.06	2.07
Modesto, CA	19	94	214,516	361	1.04	2.17
Riverside-San Bernardino, CA	18	14	1,467,227	390	1.13	0.94
Fort Lauderdale-Hollywood-Pompano Beach, FL	18	31	727,859	361	1.17	0.65
Houston-Brazoria, TX	17	10	2,147,484	391	1.00	2.30
Bakersfield, CA	16	72	303,741	368	1.01	1.64
Washington, DC/MD/VA	15	7	2,477,161	452	1.23	1.61
West Palm Beach-Boca Raton-Delray Beach, FL	14	47	474,321	370	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 (2013a). "HS elasticity" denotes housing supply elasticity, taken from Saiz (2010a).

C. *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 A.1 in the online Appendix, we provide a list of the top ten and bottom ten 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 percent higher, the number of countries with real exchange rates larger than 1 is relatively low. Australia, ranked tenth in the table, is only 7 percent 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 percent 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 (World Bank 2010).

D. *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

[3] The data series is titled "Price Level Ratio of PPP Conversion Factor (GDP) to Market Exchange Rate."

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 in 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, Cadena, and Kovak (2018) and Bryan and Morten (2019) show that these data closely match representative datasets on stocks. In this paper, we use the state-to-state migration flows for the year 2016 (IME 2016).

II. Motivating Facts

A. *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 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 a high cost of living and high wages. We make this point explicit in Section III. 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:

$$\ln\left(\frac{Imm_c}{Imm}/\frac{Nat_c}{Nat}\right) = \alpha + \beta \ln P_c + \epsilon_c, \tag{1}$$

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

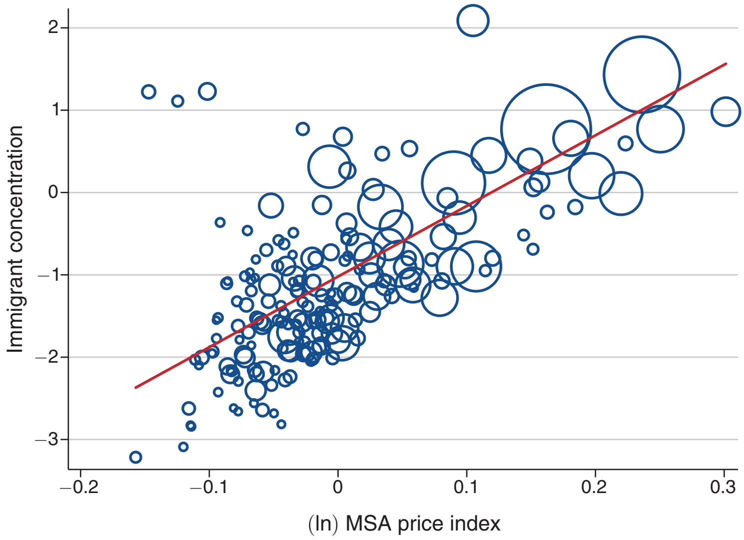

Figure 1. Immigration Concentration

Notes: This figure shows the relationship between the immigrant concentration in an 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. Circle sizes indicate MSA population.

Source: Data are from the 1990 US census.

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, and 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 WRLURI. 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 (2010a) estimates of the local housing supply elasticity (which are based both on regulations and unavailable land). The IV (instrumental variable) results suggest that the concentration of immigrants in expensive locations is not driven by reverse causality.

Table 2—Immigrant Concentration and Price Levels

	Immigrant concentration							
	OLS (1)	IV (2)	IV (3)	IV (4)	OLS (5)	IV (6)	IV (7)	IV (8)
(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^2	0.607	0.607	0.598	0.600	0.648	0.646	0.619	0.644
IV	—	WRLURI	Unavailable	Elasticity	—	WRLURI	Unavailable	Elasticity
	—		Land				Land	
First-stage F-statistic		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.

Columns 5 to 8 explore whether the results are driven by the fact that expensive cities also tend to be populous cities. Immigrants might have stronger preferences for locating in large metropolitan areas, for example because they offer amenities or products particularly attractive to immigrants (Albouy, Cho, and Shappo 2021; Handbury 2021) 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, conditioning on population does not change the fact that immigrants strongly concentrate in expensive cities.

Figure A.1 in the online Appendix shows the same type of graph as Figure 1 for each census year using different measures of likely exogenous determinants of local prices, and controlling for city population (panel B). It is apparent from the plots that immigrants concentrate in expensive cities in each year of our sample and that this result does not depend on whether we condition on population or on the measure of local prices that we use.

Robustness.—Another potential explanation for the differential sorting of immigrants across cities could be heterogeneous local labor demand. For instance, the rise of employment in low-skill service occupations such as food service workers, cleaners, or child care workers, documented by Autor and Dorn (2013), might have been particularly strong in cities with many highly paid workers. This could have made these locations more attractive to immigrants as their share of labor in low-skill service occupations is relatively large. While it is difficult to entirely rule out that this mechanism contributed to the stronger concentration of immigrants in more expensive places, we conduct a number of additional robustness checks, which indicate that heterogeneous local demand for labor is unlikely to be the main driver.

Table A.2 in the online Appendix repeats the regression in columns 5 and 8 of Table 2 limiting the sample to one of the following four education levels: high school dropout, high school graduate, some college, and college graduate. The coefficient of the local price level remains highly significant for each education group, although it is around 30 percent smaller for college graduates relative to high school dropouts. While this might indicate stronger demand for low-skilled immigrant labor in expensive cities, the smaller coefficient could also be explained by the different origin composition of college-educated immigrants, which makes them less likely to be remittance senders. For example, restricting the immigrant sample to those born in Central and South America, we find that the price coefficient in the sample of college graduates is only 9 percent lower than that in the sample of high school dropouts. We further explore the heterogeneity by origin country in the next section.

Due to occupational downgrading, the formal education of immigrants might be an imperfect proxy for employment in the low-skill service sector. Therefore, we instead rely on the actual occupation reported in the data and repeat the regression after excluding all workers (natives and immigrants) that work in one of the low-skill service occupations defined by Autor and Dorn (2013).[4] The first column of Table A.3 in the online Appendix shows that the coefficients virtually remain unchanged with respect to the full sample. Column 2 of online Appendix Table A.3 shows that we obtain similar results when we exclude service occupations and condition on low-skilled workers.

The remaining columns of online Appendix Table A.3 show that the results are also unlikely to be driven by a different composition of immigrants and natives in terms of other observable characteristics. Our findings remain robust when we include only immigrants that are likely to be documented or those that are likely to be undocumented, when we exclude 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. Online Appendix 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 eight.

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, online Appendix 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, patterns in relative wages also speak against a higher demand for immigrant labor in more expensive cities being the main explanation for immigrants' higher concentration. Online Appendix Figure A.4 plots both raw and composition-adjusted "real wages"—defined as nominal wages deflated by the native price index—of natives and immigrants as log deviations from their means

[4] These are the following: food preparation and service workers; building and grounds cleaning workers and gardeners; health service support workers; protective service workers; housekeeping, cleaning, and laundry workers; personal appearance workers (such as hairdressers and estheticians); child care workers; recreation and hospitality workers; and other personal service workers. Around 5 percent of natives and 8 percent of immigrants are employed in one of these occupations.

against the city price level.[5] While real wages of natives are slightly increasing in the city price without adjustment, they are completely uncorrelated to prices after adjusting for demographic characteristics. In contrast, both before and after adjustment, immigrants' "real wages" *decrease* in the city price. Without our channel, if there were a relatively higher demand for immigrant labor in more expensive cities, we would expect their gradient of composition-adjusted real wages to be at least as high as that of natives. We think, instead, that these patterns reflect the fact that price deflators for immigrants need to take into account that part of their income is spent in their home countries.

Furthermore, in the online Appendix, we explore the role of the demand for labor more thoroughly by using the gap in composition-adjusted wages between natives and immigrants instead of the immigrant concentration as dependent variable, in our regression analysis. We confirm that this gap has a strong negative relationship with the city price level (see online Appendix Table A.5). Thus, relative to *comparable* natives, immigrants earn less—not more—in more expensive cities, discarding an explanation based on the heterogeneous demand for labor. This evidence on wages is also in line with evidence provided by Dustmann, Ku, and Surovtseva (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 this analysis we also control for the fact that immigrants and natives may be imperfect substitutes in production as we explain in detail in the online Appendix.

B. *Immigrant Heterogeneity*

In this section, we explore whether there is heterogeneity in how much immigrants concentrate in expensive locations. We use different datasets 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. The concentration of immigrants in expensive cities attenuates somewhat for second- and (likely) third-generation immigrants.

We also explore in this section whether this heterogeneity can be explained by other 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.

[5] Composition-adjusted wages are residuals from a regression of the log weekly wage on dummies for sex, race, marital status, education level, and experience level.

To visually explore the heterogeneity by country of origin, we start by estimating equation (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 8 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.[6]

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 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. The plot 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.[7] We proxy local prices with GDP per capita at the state level.[8] 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 (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:

$$(2) \quad \ln\left(\frac{Imm_{c,o,t}}{Imm_{o,t}} / \frac{Nat_{c,t}}{Nat_t}\right) = \beta_1 \ln P_{c,t} + \beta_2 \ln RER_{o,t} + \beta_3 \ln P_{c,t} \times \ln RER_{o,t} + \beta_4 Net_{c,o,t} + \delta_t + \delta_o + \delta_c + \epsilon_{c,o,t},$$

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

[6] The reason we use the reduced-form version of column 8 in Table 2 rather than the IV specification is because we cannot compute local prices at the yearly level with CPS data, which are the data used in panel B and panel D of Figure 2.

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

[8] GDP data are taken from the Bureau of Economic Analysis (2016) for the United States and from INEGI (2016) for Mexico.

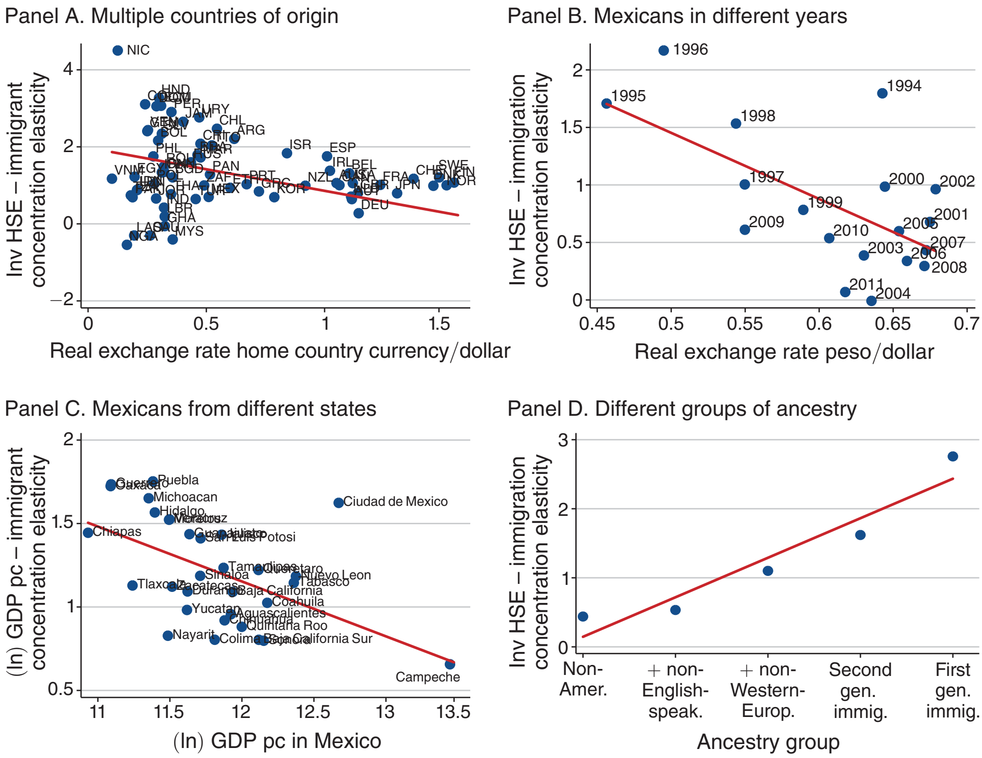

FIGURE 2: HETEROGENEITY IN THE CITY PRICE ELASTICITY OF IMMIGRANT CONCENTRATION

Notes: Based on census/ACS data, panel A plots the elasticity of the immigrant concentration with respect to the MSA inverse housing supply elasticity (HSE) for each 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 HSE for each year as a function of the Mexico-US real exchange rate. Based on Matricula Consular data on migrant flows from Mexican states to US states, panel C shows the concentration of Mexicans across US states in terms of GDP per capita (pc) as a function of the GDP per capita in the Mexican state of origin. Based on CPS and census/ACS data, panel D plots the elasticity of the concentration of different ancestry groups (relative to individuals outside this group) with respect to the MSA inverse HSE. The first three points correspond to the following ancestry groups, respectively: outside North America; outside North America and outside English-speaking countries; outside North America, outside English-speaking countries, and outside Western European countries. Second-generation immigrants are defined as those with at least one parent born abroad.

(PPML) regression model in order to deal with the incidence of zeros (Santos Silva and Tenreyro 2006).[9] 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.[10] The estimate of interest is β_3. A negative estimate of β_3 indicates that immigrants from cheaper countries tend to concentrate

[9] 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 percent of all immigrants in the sample.

[10] In particular, we allocate the total immigrant population from a certain origin according to its distribution across MSAs ten years before and then divide this predicted immigrant stock by current city population (natives

Table 3—Immigrant Concentration and Price Levels, Heterogeneity by Country of Origin

	Immigrant concentration							
	PPML (1)	PPML (2)	PPML (3)	PPML (4)	PPML (5)	PPML (6)	PPML (7)	PPML (8)
(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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
MSA fixed effects	No	No	No	Yes	No	No	No	Yes
Observations	37,740	37,740	37,740	37,740	37,740	37,740	37,740	37,740
R^2	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, 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.

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.[11]

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 six. 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

plus immigrants) to get the predicted network. Results are virtually identical when always allocating based on the 1980 distribution.

[11] The coefficient β_2 captures the effect of the real exchange rate on the *average* concentration of immigrants from origin o at time t across cities. Note that, if immigrants are distributed exactly like natives, this average would be equal to one (or zero when taking logs). However, as follows from our argument, immigrants tend to be more concentrated in expensive cities than natives and hence we expect $\beta_2 > 0$.

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 for these results in the online Appendix. Online Appendix Table A.6 explores the robustness of our results to introducing immigrant networks through different parametric and nonparametric specifications. Online Appendix Table A.7 investigates the sensitivity of our results to flexibly controlling for population levels. Online Appendix Table A.8 shows the results by groups of countries. All these tables confirm that our results are robust. Taken together, they 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 of 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.

One source of heterogeneity could be the current length of stay in the host country. First-generation immigrants are more likely to have return plans or family members in the country of origin and thus send more remittances. In contrast, second- and third-generation immigrants may have already lost part of the relationship to the country of origin. To investigate this idea, we use information on the birthplace of a respondent's parents, which is available in the CPS, and the self-reported country of "ancestry," which is available in the census and ACS.

Panel D of Figure 2 shows the various coefficients we obtain when using the concentration of different ancestry groups (relative to those outside the group) as well as that of second- and first-generation immigrants as the dependent variable in equation (1).[12] Reading the x-axis from left to right, we start with the concentrations of different groups of natives with foreign ancestry, ordered by migration episodes. The first group includes all individuals reporting an ancestry from a country outside North America. The second group excludes individuals with ancestry from English-speaking countries from the first group. The third group also excludes those with ancestry from Western Europe. The plot suggests that when we exclude ancestry groups with more distant migration episodes, those remaining in the foreign ancestry group become more concentrated in cities with high housing supply elasticities. That is, we find that when moving from the first ancestry group to first-generation immigrants, the estimated coefficient steadily increases from 0.44 to 2.76. The fact that natives with foreign ancestry are also more likely to be located in more expensive cities can probably be explained by the stickiness of the location choices across generations. It is worth highlighting that the difference in the elasticity of the concentration between first and second generation immigrants (2.76 and 1.62, respectively) is statistically significant.

[12] For this, we again estimate the reduced-form version of the specification shown in column 8 in Table 2 because we cannot compute local prices at the yearly level in the CPS data.

Table 4—Immigrant Concentration and Price Levels, Alternative Sources of Country of Origin Heterogeneity

	Immigrant concentration					
	Return rates		Remittances		Pre-'82 vs post-'82	
	PPML (1)	PPML (2)	PPML (3)	PPML (4)	PPML (5)	PPML (6)
(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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Origin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,185	37,185	35,520	35,520	37,185	37,185
R^2	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 (1982), 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.

Another alternative is to explore heterogeneity at the country level. For this, 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 are more likely to be documented thanks to the 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 (2019b), who estimate return migration rates for 67 of the origin countries in our sample.[13] Results are shown in columns 1 and 2 of Table 4. 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

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

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 are hard to obtain.[14] 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.[15] Using this information, which is only available from 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 the 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 cutoff year of 1982. We use the immigrant concentration computed based on arrivals over this period as dependent variable, although the results expand to include 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 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 III 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.[16]

[14] The 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).

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

[16] 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

C. *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 United States. 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 percent 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 percent, which results in \$540 billion. Thus, the remittance share of wage income is a very sizable 20 percent.[17]

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 datasets to investigate whether immigrants consume less locally than natives: the CEX and the census. The former allows us to 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 percent of total expenditures (Davis and Ortalo-Magne 2011).

Section IVA). In online Appendix Table A.10, we regress these estimated parameters on exchange rates and find a strong negative correlation, lending further support to our proposed mechanism.

[17] Considering also nonwage income, the remittance share would be around 18 percent. For this exercise, we include all immigrants aged 18 to 65.

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

$$(3)\quad \ln TotalExpenditure_{i,c,t} = \alpha + \beta Mexican_{i,c,t} + \sum_k \gamma_k HHIncomeCategory\, k_{i,c,t} + \eta X_{i,c,t} + \delta_c + \delta_t + \epsilon_{i,c,t},$$

where the dependent variable is the quarterly total expenditure at the household level.[18] 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; $X_{i,c,t}$ 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.[19]

Results.—The results, reported in panel A of Table 5, suggest that, unconditionally, Mexican households consume on average around 33 percent less than non-Mexican households, and as much as 38 percent when we force within-state comparisons (column 2). In column 3, we include income controls, which reduce the estimate to 15 percent. When we add all the household level controls in column 4, we find that Mexican households consume around 22 percent less locally than non-Mexican households. With savings close to 0 percent (in the early 2000s the savings rate was around 2 percent), 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.[20]

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 percent to 20 percent 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 tenants. In Table A.9 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) but using a continuous

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

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

[20] As can be seen in data from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/PSAVERT), the aggregate personal savings rate has fluctuated between 2 percent and 12 percent since 1980. See also Dynan, Skinner, and Zeldes (2004) for a discussion on how savings are lower for low-income households.

TABLE 5—IMMIGRANTS' EXPENDITURE

Panel 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 fixed effects	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	105,975	105,975	105,975	105,975	105,975	105,975	105,975	105,975
R^2	0.031	0.063	0.301	0.314	0.018	0.079	0.226	0.249

Panel 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	−0.490	−0.407	
	(0.024)	(0.023)	(0.018)		(0.057)	(0.044)	(0.032)	
(ln) RER				0.068				0.138
				(0.018)				(0.022)
(ln) household income			0.277	0.237			0.329	0.295
			(0.004)	(0.005)			(0.022)	(0.022)
MSA fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	699,699	699,699	699,699	149,903	699,699	699,699	699,699	149,903
R^2	0.294	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 CEX 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.

measure of income and MSA fixed effects.[21] When including these fixed effects in the second column of panel B, we find that immigrant households spend around 14 percent 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 percent.

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 III, 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 0.5 fewer rooms than units

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

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 from more expensive countries spend more income on housing in general (and space in particular) in the host country, conditional on observable characteristics. We return to these results in Section IIID 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.

III. 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.

A. *Model Setup*

Utility and Location Choices.—The utility of individual i from country of origin j in city/location c is given by

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

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 nontradable goods C_H and foreign goods C_F, respectively. The elasticity of substitution between local nontradable and foreign goods is denoted by σ. Note that C_H represents the consumption of housing and other nontradable goods which need to be consumed in location c. For simplicity, we will henceforth refer to C_H as *housing*. It is worth noting that, as long as $\sigma < \infty$, housing cannot be perfectly substituted with foreign consumption. Note also that the amount of housing services consumed—which can be thought of in terms of both size or quality of the housing unit—will depend on the relative prices of C_H and C_F.[22]

The variable Z_{jc} denotes the utility derived from local amenities, which consists 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

[22] We opt for allowing only nontradable goods to be substitutable with foreign goods for three main reasons. First, tradable goods to a large extent contain periodically purchased nondurable goods like food products that can barely be substituted with foreign 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.

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 $j = N$.[23]

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 one. The demand for each good is given by

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

where

$$P_{jc}(\beta_l, \beta_f) = \left(\beta_l^{\sigma} p_c^{1-\sigma} + \beta_f^{\sigma} p_j^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{4}$$

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 the online Appendix):

$$\ln V_{ijc} = \ln V_{jc} + \ln \epsilon_{ijc} = \ln Z_{jc} + \ln w_c - \beta \ln P_{jc}(\beta_l, \beta_f) + \ln \epsilon_{ijc}. \tag{5}$$

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 shocks, the outcome of this maximization yields:[24]

$$\pi_{jc} = \frac{V_{jc}^{\theta}}{\sum_k V_{jk}^{\theta}} = \left(\frac{V_{jc}}{V_j}\right)^{\theta}, \tag{6}$$

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 $V_j = \left(\sum_k V_{jk}^{\theta}\right)^{1/\theta}$, which is the expected value, or, in short,

[23] There are alternative interpretations for what foreign consumption C_F represents. It could include consumption of nontradables 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.

[24] 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 in Section IV.

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 (5) and summing over j, we then obtain the overall labor supply in city c as

$$L_c = w_c^\theta \sum_j \left[\left(\frac{Z_{jc}}{P_{jc}^\beta V_j} \right)^\theta L_j \right] = w_c^\theta L \sum_j \left[\left(\frac{Z_{jc}}{P_{jc}^\beta V_j} \right)^\theta \frac{L_j}{L} \right]. \tag{7}$$

Equation (7) 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:

$$Y_c = A_c L_c^\alpha K_c^\eta \left(T_c^B \right)^{1-\alpha-\eta}, \tag{8}$$

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.[25] 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:

$$L_c = \left(\frac{\alpha^{1-\eta} \eta^\eta}{r^\eta} \frac{A_c}{w_c^{1-\eta}} \right)^{\frac{1}{1-\alpha-\eta}} T_c^B. \tag{9}$$

As is standard in these models, equation (9) implies that more productive locations and locations with more land available for businesses have a higher demand for labor.

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:

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

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

where $1-\zeta_c$ is the weight of land in the production of housing. We assume land is owned by absentee landlords.[26]

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

$$Y_c^H = T_c^H p_c^{\gamma_c}, \tag{10}$$

where $\gamma_c = \frac{\zeta_c}{1-\zeta_c}$ 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 nontradables in the country of origin. Local housing prices are implicitly defined by market clearing in each city:

$$T_c^H (p_c)^{\gamma_c} = \left(\beta \frac{w_c}{p_c} L_c\right)\left[\frac{L_{Nc}}{L_c} + \sum_{j \neq N} \beta_l^{\sigma}\left(\frac{p_c}{P_{jc}}\right)^{1-\sigma}\frac{L_{jc}}{L_c}\right]. \tag{11}$$

Note that this equation reflects one of the differences between our model and standard spatial equilibrium models such as 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. Being explicit about how the equilibrium condition in housing is generated has important advantages in our context. First, it allows us to study the effect of changes in the composition of the demand for housing and to be precise when we compare them to the effect of changing the housing supply elasticity (γ_c). We provide more details on this point in Section IVA and in the online Appendix. Second, 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 1: *The spatial equilibrium is defined as follows:*

(*i*) *Workers decide where to live and how much to consume of each good.*

(*ii*) *Firms decide how many workers to hire to maximize profits.*

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

(*iii*) *Developers decide how much housing to supply.*

(*iv*) *Goods*, *labor*, *and housing markets clear.*

B. *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 IIIC, 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 1. *Within the consumption of nontradables*, *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 (6) to obtain the following result.

PROPOSITION 1: *The immigrant concentration is given by equation* (12), *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, *if and only if* $\sigma > 1$.

$$\ln\frac{\pi_{jc}}{\pi_{Nc}} = \theta\left(\ln Z_{jc}^{Net} + \beta\ln\frac{p_c}{P_{jc}}\right). \tag{12}$$

PROOF:

See online Appendix.

Proposition 1 is directly linked to the facts that we report in Section II. 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 (12) 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).

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 (6) to obtain a relationship between wages and aggregate welfare for workers from each country of origin:

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

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

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

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 $\bar{Q}_j \equiv \left[\sum_c Q_{jc}\left(\frac{L_{jc}}{L_j}\right)^{\frac{1}{\theta}}\frac{L_c}{L}\right]$, 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

$$V_j = \alpha\frac{Y/L}{\bar{Q}_j}. \tag{13}$$

Note that equation (13) 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 (7) and solve for the wage:

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

We then substitute this expression into the labor demand (9), solve for L_c, and then aggregate labor across locations to finally solve for aggregate output:[27]

$$Y = \left(\frac{\eta}{r}\right)^{\frac{\eta}{1-\eta}} L^{\frac{\alpha}{1-\eta}}\left\{\sum_c\left[A_c\left(\left(\sum_j s_j\left(\frac{\bar{Q}_j}{Q_{jc}}\right)^{\theta}\right)^{\frac{1}{\theta}}\right)^{1-\eta}\left(T_c^B\right)^{1-\alpha-\eta}\right]^{\frac{1}{\psi}}\right\}^{\frac{\psi}{1-\eta}} = AL^{\frac{\alpha}{1-\eta}}, \tag{14}$$

[27] From

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

we obtain

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

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

Intuitively, equation (14) says that aggregate output can be written as aggregate labor, raised 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 comparing equation (14) to the one that would prevail without immigrants in the economy:

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

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.*

C. *Estimation*

We estimate the model by nonlinear least squares based on equation (12). 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. The parameters 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.[28] Immigrants from origins with lower prices devote higher fractions of their income to home-country goods if $\sigma > 1$. Finally, θ governs 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 (2013a), 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}:

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

where, as in Section IIB, 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 a mean of zero. 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:

$$\ln\frac{\pi_{jc}}{\pi_{Nc}} = \theta\left[\phi Net_{jc} + 0.4\ln\frac{p_c}{P_{jc}\left(\sigma,\beta_f\right)}\right] + \theta\nu_{jc}. \tag{15}$$

To derive a consistent estimator of $\lambda \equiv \left(\sigma,\beta_f,\theta,\phi\right)$, we impose the orthogonality condition $E\left[\nu_{jc}|p_c,P_{jc},Net_{jc}\right] = 0$. 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 IV. In particular, we set the economy-wide average of immigrants' expenditure share on origin

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

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	
Nontradable goods spending share	β	0.40	
Return to capital	r	0.05	
Estimated parameters		Value	SE
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	12.89	5.53
Sensitivity to immigrant networks	ϕ	1.30	0.38

Notes: This table shows the estimates taken from Hsieh and Moretti (2019) and the structural parameters of the model estimated by nonlinear least squares using equation (15). 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.

goods equal to the remittance share of 20 percent that we identified in the data.[29] This uniquely pins down β_f as a function of σ.[30] Hence, we define the estimator as

$$(16) \qquad \hat{\lambda} \equiv \arg\min_{\lambda} \sum_j \sum_c \left[\nu_{jc}(\lambda)\right]^2 \quad \text{s.t.} \quad \frac{\sum_j \sum_c \omega_{jc} p_j C_{F,jc}}{\sum_j \sum_c \omega_{jc} w_c} = 0.2,$$

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

Table 6 presents the parameters taken from the literature and the ones we estimated. 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 12.9, which is somewhat higher than other estimates in the literature (see Diamond 2015; Monras 2015; Caliendo, Dvorkin, and Parro 2019). 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 total factor productivity (TFP), defined as the composite $A_c\left(T_c^B\right)^{1-\alpha-\eta}$, 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 (9).[31] The values of Z_c can be obtained by removing the sum from (5), 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.[32]

[29] 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.

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

[31] Wages are measured as average residuals in city c in the year 1990 obtained from a Mincerian regression.

[32] 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 $\left(p_c^{\beta}/w_c\right)\left(L_{Nc}/L_N\right)^{1/\theta}$.

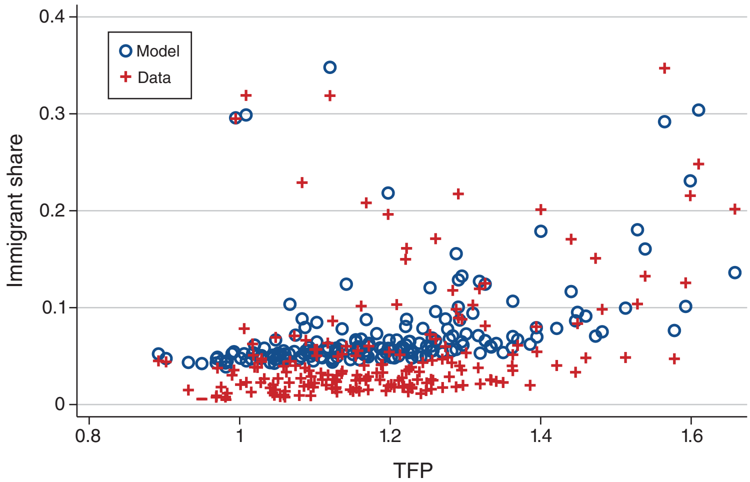

FIGURE 3. MODEL GOODNESS OF FIT

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.

Further, when conducting counterfactual simulations, we make use of the housing market equations (10) and (11) to calculate the new equilibrium house prices resulting from changes in housing demand combined with the housing supply elasticities from Saiz (2010a). For this, we compute the land used for housing T_c^H from equation (11), given the parameters and the values observed in 1990 for native and immigrant populations, wages, and prices.

D. *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.[33]

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 already identified as outliers in Figure 1. In quantitative terms, the model is able to explain 74 percent of the variation in the immigrant 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

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

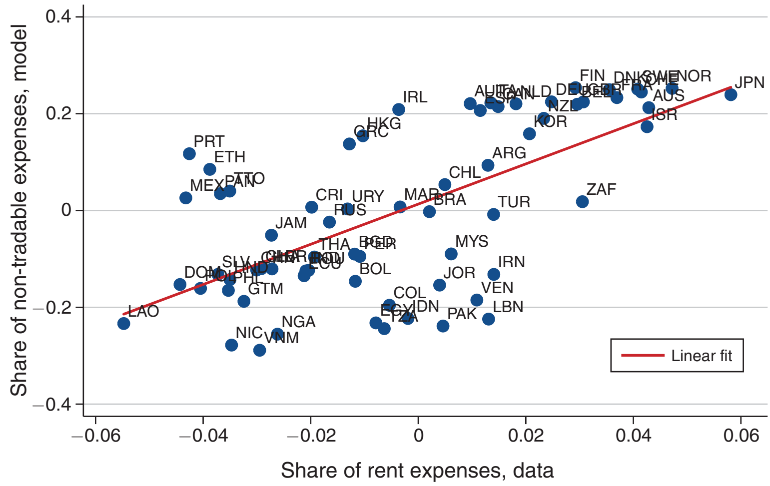

FIGURE 4. NONTARGETED MOMENTS I: SHARE OF EXPENDITURES ON LOCAL NONTRADABLE GOODS

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 nontradable goods predicted by the model (both as deviations from the mean).

origins, more likely to choose high-price locations. If we ignore this channel by setting $\beta_f = 0$ for all immigrants and we only allow immigrants to differ from natives in their valuation of networks, the model is only able to explain 39 percent of the variation in the immigrant share in the data.

Nontargeted 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 nontradable 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 IIC. 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 nontradable expenditure from its average in the model in Figure 4. We find a tight significant relationship between data and model predictions.

Nontargeted Moments II: Immigration over the 1990s.—As a second check on nontargeted 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-nineteenth century.

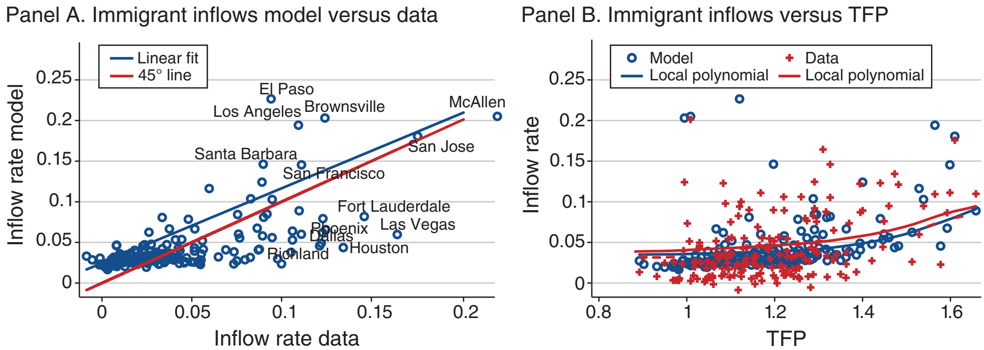

Figure 5. Nontargeted Moments II: Immigrant Population Changes Predicted by the Model and Observed in the Data

Notes: Panel A shows for each MSA the immigrant inflow rate between 1990 and 2000 (calculated as change in immigrant population divided by overall population in 2000) in the data (x-axis) and the corresponding model predictions (y-axis). A 45° line and a linear fit are plotted in red and blue, respectively. Panel B plots the data and model predictions against TFP with the respective local polynomial fit.

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.[34] Thus, the total population share of immigrants rose from 12 percent to 19 percent. 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.

Figure 5 shows the comparison between the model predictions and the data. Panel A plots the change in immigrant population in each location over the 1990s relative to the total population, which we label as the inflow rate, predicted by the model against the data. The graph shows a positive correlation between the model predictions and the data counterpart. The fitted line is close to the 45° line. Panel B shows the same variables but plots both model predictions and data against our measure of local productivity. The graph shows that the relationship between immigrant inflows over the 1990s predicted by our model and local productivity is very similar to the one we see in the data.

In order to separately quantify the contribution of the different channels operating in the model, we conduct two additional counterfactual simulations. In the first one, we assume that there is no heterogeneity in consumption or amenities between natives and incoming immigrants (i.e., $\beta_f = \phi = 0$). In the second one, we assume that natives and immigrants only differ in that immigrants value network

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

amenities. This contrasts with the full model where immigrants derive utility from network amenities and goods consumed in their origin countries purchased with local income. Figure A.5 in the online Appendix 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 graphs show that only when we include our mechanism the model predicts reasonably well the patterns of immigrant and native population changes over the 1990s.

In sum, Figure 5 and online Appendix Figure A.5 suggest that the origin consumption channel goes a long way to explain the observed patterns in immigrant and native population growth rates across US cities during the 1990s.

IV. 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 distribution of population.

A. *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. The fact that some of these constraints on the supply of housing likely come from local political decisions is what justifies the label "misallocation." Our framework suggests that immigrants' distinct consumption preferences lead to a reduction in this labor misallocation. We quantify the aggregate role of immigration in this section.

To do so, we conduct several counterfactual simulations, in which we vary the assumptions on immigrants' preferences and we compute the change in aggregate output and native welfare with respect to a reference model where natives and immigrants are identical. Furthermore, in order to put the size of the effects of immigrants' distinct location choices into perspective, we also calculate the output and welfare effects of relaxing constraints on housing markets, either in the main culprits of the spatial misallocation of labor identified in Hsieh and Moretti (2019)—New York City, San Francisco, and San Jose—or in a broader set of cities.

We show these results in Table 7. The upper panel of Table 7 shows the percentage change in output and welfare when we set the housing supply elasticity in New York City, San Francisco, and San Jose to that of the median city in the United States.[35] Our model implies aggregate output gains of 0.4 percent in this case.[36] Similarly,

[35] Saiz (2010a) estimates of the housing supply elasticities are 0.76, 0.66, and 0.76 for these three cities and the median estimate across all US cities in our sample is 2.14.

[36] Note that we obtain a different number than that reported in Hsieh and Moretti (2019). This is so because the reduced-form housing supply equation assumed in Hsieh and Moretti (2019) is such that a change in the housing supply elasticity is equivalent in our model to both a change in the land available for housing (T_c^H) and the housing supply elasticity (γ_c). In our context, we cannot assume Hsieh and Moretti's (2019) housing supply equation because it is important in our context to specify the demand for housing of natives and immigrants. We provide additional details on this point in the online Appendix.

TABLE 7—CHANGES IN OUTPUT AND WELFARE RELATIVE TO COUNTERFACTUAL WITHOUT NATIVE-IMMIGRANT HETEROGENEITY

	Output (% change)	Native welfare (% change)
Aggregate effect of changing the housing supply elasticity to the median		
in New York City, San Francisco, San Jose	0.40	1.38
in all cities	0.46	3.30
Aggregate effect of immigration implied by		
Baseline model	0.46	1.59
Baseline model with θ_N and θ_I from literature	0.30	1.49
Model with $\sigma = 1$ and origin-specific $\beta_{f,j}$	0.36	1.45
Model 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.

we compute how much aggregate output changes if we change the housing supply elasticity in every city to the median. In this case, we obtain that aggregate output would experience only a somewhat larger increase of 0.46 percent.

These output gains reflect the reduction in the spatial misallocation of labor identified in Hsieh and Moretti (2019). These gains are due to the fact that more productive cities tend to have more inelastic supplies of housing. Hence, equalizing the housing supply elasticity to that of the median city leads to an expansion of the supply of labor in relatively more productive cities. The welfare effects are even larger than the output effects since they additionally reflect the decrease in the cost of living implied by less constrained housing markets. These numbers provide a benchmark to understand the effects of immigration on aggregate output and native welfare.

The first row in the lower panel of Table 7 presents the results of comparing our baseline model with and without the immigrant consumption channel. The implied shift in the equilibrium distribution of workers across cities leads to an increase in output of 0.46 percent. Hence, this effect is of a similar size as the one obtained by setting housing supply elasticities to the median in all locations. The fact that immigrants consume in part in their origin and, hence, demand lower housing services, also reduces, on average, the pressure on house prices. As a result, we again find a larger effect on welfare than on output. Our estimate of the immigrant effect is 1.59 percent, which is around half of that of setting all housing supply elasticities to the median and similar to setting the housing supply elasticity of New York City, San Francisco, and San Jose to the median.

In the following two rows, we estimate the effect of immigration using alternative parameterizations of the model. First, we assume that θ, the parameter governing the sensitivity of workers' location choices to dispersion in indirect utilities across cities, is different for natives (θ_N) and immigrants (θ_I). Instead of estimating these parameters, we use estimates provided by Diamond (2015).[37] In particular, we set

[37] 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

$\theta_N = 5$ and $\theta_I = 7.8$, and then reestimate the remaining parameters of the model.[38] Second, we investigate an alternative to our baseline model where we assume that $\sigma = 1$ and allow an origin-specific share of foreign expenditures to rationalize the distribution of immigrants across locations. It is worth noting that this alternative model that loads all the observed heterogeneity on preferences (conditional on immigrant networks) also allows to gain more confidence on our own baseline model. In Table A.10 in the online Appendix, we regress the share of income spent at origin $(\beta_{f,j})$ 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 origins.

Looking at the output and welfare effects for each of these two alternatives, we obtain estimates that are similar to, albeit a bit smaller than, our baseline model. 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 estimate of 12.9. 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 the 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 online Appendix Figure A.5), we now obtain a small negative output effect of 0.04 percent. 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.

B. *Counterfactual Analysis: Local Effects*

So far, we have focused on the aggregate output and welfare effects of immigrants' consumption channel. In this final section, we investigate in more detail how these aggregate effects are generated by looking at the population effects induced by

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 that lies between the estimates reported in columns 1 and 2 of that table. Other estimates in the literature, such as the ones provided by Notowidigdo (2020), point in the same direction. Using any of the alternative values does not significantly affect our results.

[38] 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).

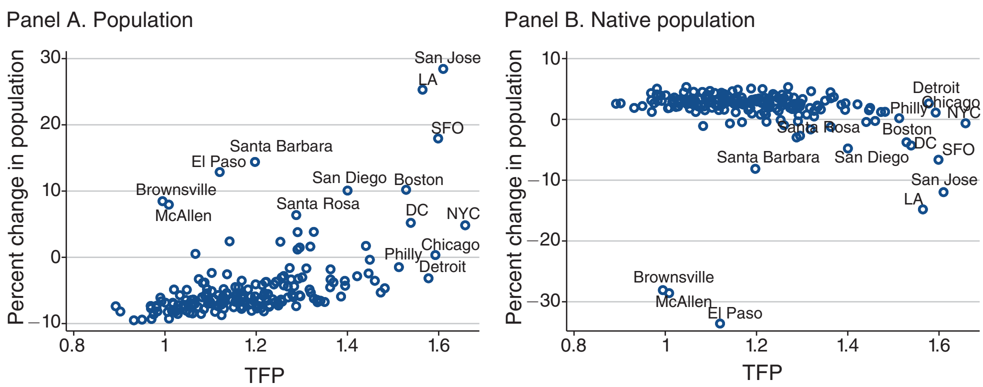

Figure 6. Contribution of Immigrant-Native Heterogeneity to City Population Growth and Wages

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.

migrants' choice of location. 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 percent and 25 percent, respectively, while other highly productive cities like San Diego; Boston; Washington, DC; or New York City grow between 5 percent and 10 percent. Moreover, a range of less productive cities with large Mexican or Latin American communities in Texas and California grow around 10 percent thanks to their network amenities. In contrast, many other cities at the bottom of the TFP distribution lose up to 10 percent of their population. It is worth noting that, given the existing positive correlation between local productivity and housing supply elasticities, these numbers are also similar to the ones we would obtain when changing existing housing supply elasticities to the median city.

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 number 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 percent to 15 percent in terms of native population, while cities on the Mexico-US border lose around 30 percent 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.

V. 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 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 percent and 1.6 percent, 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 (2010a) does not provide estimates of housing supply elasticities for nonurban 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.

The evidence and the model presented in this paper have implications for migration policy. Migration policies that induce family migration, and hence, reduce the incentives to remit income, likely result in a wider geographic spread of migrants. In contrast, temporary migration programs, or migration policies that restrict the number of family members included in a migration visa, are likely to have the opposite effect.

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