Immigrants' Residential Choices and Their Consequences

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Abstract

This paper investigates the causes and effects of the spatial distribution of immigrants across US cities. We document that: a) immigrants concentrate in large, high-wage, expensive cities, b) the earnings gap between immigrants and natives is higher in larger, more expensive cities, and c) immigrants consume less locally than natives. In order to explain these findings, we develop a quantitative spatial equilibrium model in which immigrants consume a fraction of their income in their countries of origin. Thus, immigrants care not only about local prices, but also about price levels in their home countries. This gives them a comparative advantage relative to natives for living in high-wage, high-price, high-productivity cities, where they also accept lower wages than natives. These incentives are stronger for immigrants coming from lower-price index countries of origin. We rely on immigrant heterogeneity to estimate the model. With the estimated model, we show that current levels of immigration have reduced economic activity in smaller, less productive cities by around 5 percent, while they have expanded it in large, productive cities by around 6 percent. This has increased total aggregate output per worker by around 0.3 percent. We also discuss the welfare implications of these results.

JEL Categories: F22, J31, J61, R11.

Keywords: Immigration, location choices, spatial equilibrium.

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1 Introduction

We consume mainly where we live; however, not all goods are produced locally. Both tradable and non-tradable local goods constitute the main elements of the price index that people face when living in a particular location. Since Krugman (1991) and the extensive literature that followed, this has constituted the basis for thinking about the distribution of people across space.

While this simplification of how people consume may be accurate for most of the population, immigrants spend a considerable portion of their income in their home countries. For example, using German data, Dustmann and Mestres (2010) estimate that immigrants send around 8 percent of their disposable income back to their home countries, and this share is even larger for immigrants that plan to return home. Thus, immigrants care not only about the local price index but also about the price index in their home countries.

Local price indices vary considerably between US cities. In New York City, for instance, they are around 20 percent higher than the national average–mainly due to housing.[1] At the same time, nominal incomes are also much higher in New York than in smaller, lower-price-index cities. These higher wages "compensate" for the higher living costs, as predicted in the Rosen (1974)-Roback (1982) spatial equilibrium model.

Given that immigrants care about both local prices and prices in their countries of origin while natives may be concerned solely with local ones, natives and immigrants potentially have different incentives for choosing which metropolitan area to live in.[2] For example, an immigrant may find it particularly advantageous to live in a city like New York. All else being equal, for immigrants in New York City, the income left after paying for local goods is likely to be higher than in a smaller, lower-wage, less expensive city.[3] In this paper, we show how this mechanism affects the residential choices of natives and immigrants in the United States both empirically and quantitatively through the lens of a model.

In the first part of the paper, we use a number of different data sets to document four novel and very strong empirical regularities in the United States. First, we report that in recent decades, immigrants have concentrated in large, expensive cities.[4] Second, the gap in earnings between natives and immigrants is *greatest* in these cities. Third, immigrants consume less than natives locally. And fourth, there is significant heterogeneity across different groups of immigrants. In particular, we show, using across *and* arguably exogenous within-origin variation, that these patterns in relative location choices and native-immigrant wage gaps are stronger for immigrants coming from lower-income, low-price-index countries.[5]

[1] See Table 1. San Jose's local price index is around 50 percent above the national average. Local prices of tradable goods tend to be lower in large cities once the diversity of products available is taken into account (Handbury and Weinstein (2015)), though we do not take this into account in this paper.

[2] A paper that also uses differences in preferences to understand differences between regions is Atkin (2013). Our focus is very different than Atkin's, however, since we study the spatial distribution of immigrants and natives based on their preferences for consuming in their country of origin, while Atkin (2013) studies how acquired local preferences affect migrants' nutrition and welfare.

[3] More generally, any neoclassical spatial equilibrium model where immigrants and natives have similar preferences but where immigrants have an extra normal good to consume–home country goods–would deliver this result. See the discussion at the beginning of Section 4.

[4] These cities, as is well known in the literature and we also document with our data, tend to pay higher nominal wages. See for example Combes and Gobillon (2014) and Glaeser (2008). We also document this fact in this paper.

[5] For this exercise we use Census, ACS and price levels at origin estimates by the World Bank for 1990, 2000, and 2010 and 89 different countries of origin and we rely in changes in the real exchange rate between the United States and the origin country in these 3 years.

We also obtain this result using higher frequency within-origin real exchange rate variation between Mexico and the United States. When the price of the peso is low relative to the dollar, i.e., when it is relatively cheaper to consume in Mexico, Mexicans concentrate more in large, expensive cities, and the native-immigrant earnings gap is higher.[6] We also show that these patterns are stronger for Mexicans closer to the US-Mexican border, in line with the idea that ties to the home country are stronger for immigrants physically closer to their home country (Hanson, 2001). Finally, in Appendix B.1 we show that these patterns are attenuated in the case of immigrants that have spent a considerable amount of time in the United States and *cannot* be explained by immigrant networks, differences in human capital between natives and immigrants, or imperfect immigrant-native substitutability within narrowly defined education groups.

In the second part of the paper, we explain these strong empirical regularities with a quantitative spatial equilibrium model where preferences for locations depend on country of origin-specific price indexes. With this model we then investigate the role that immigration plays in shaping the distribution of economic activity across locations and, through this mechanism, its contribution to the general equilibrium. In the model, natives consume only locally, whereas immigrants also consume in their home country and therefore also care about price levels there.[7] Hence, an immigrant requires lower compensation in nominal wages in order to move to an expensive city. This implies that immigrants concentrate in expensive cities and that, if wages partly reflect the value of living in a city, the native-immigrant wage gap is higher in high local price index locations.[8] Some degree of substitutability between home and local goods allows this mechanism to be stronger for immigrants coming from poorer countries, which is in line with the data both when we compare location and wage patterns across countries of origin and when we relate these to exchange rate variation.

We estimate the key parameters of the model to match relative population and wage data across cities between natives and immigrants for each country of origin and we complement these estimates with parameters from the prior literature to perform quantitative exercises (specifically, we use Albouy (2016), Combes and Gobillon (2014), and Saiz (2010)). In particular, we find that the parameter governing immigrants' weight for the home country is around 10 percent. This means that the distribution of immigrants across locations and their wages relative to those of natives is consistent with immigrants consuming around 10 percent of their income in their country of origin. This aligns very well with the direct evidence provided using consumption data, which is not used when estimating the model. This magnitude suggests that the home country is economically important to immigrants and has a strong influence on where they decide to settle and their wages, which in turn has important consequences for the host country.

We use our estimated model to compute the counterfactual distribution of population, wages, and

[6]We focus on Mexicans because this is the largest immigrant group, and thus, there are enough movers so that we can estimate location choices across US cities for each year. See the exact details of this exercise in section 3.1.4.

[7]Consumption at home can happen in various forms. It could be that immigrants spend a portion of their time in the home country, or that they send remittances to their relatives, or that they save for the future while intending to return to their country of origin. All these are equivalent from the point of view of the model. See Dustmann (1997) for savings decisions and return migration.

[8]In order to obtain this result, wage differences between workers cannot be competed away. This means that we depart from standard perfectly competitive models of the labor market and instead consider wage bargaining. See Becker (1957) and Black (1995).

economic activity when immigrants do not care about consuming in their home country. This allows us to quantify how immigrant location choices may affect host countries. Our main finding is that there is a significant redistribution of economic activity from small, unproductive cities to large, productive ones as a consequence of immigrants' location choices.[9] With current levels of immigration, we show that low-productivity cities lose as much as 5 percent of output, while more productive ones gain as much as 6 percent. We also show that some natives who would otherwise live in these more productive cities are priced out of the housing market, and that the ones who stay have *higher* nominal incomes than they would without immigration. In sum, immigration contributes to increasing *nominal* inequalities across metropolitan areas. In aggregate, we estimate that current levels of immigration expand total output per capita by around 0.3 percent.[10]

We conclude our analysis by exploring how these changes in economic activity across space affect natives' welfare. There are essentially three groups of natives: workers, landowners, and firm owners. On the one hand, the model suggests that native workers in large, expensive cities lose in terms of welfare because immigrants' location choices put pressure on housing markets and this pressure is not compensated for by higher nominal incomes. On the other hand, landowners and firm owners in large cities benefit from immigration.

This paper extends the seminal work of Borjas (2001).[11] According to Borjas (2001), immigrants "grease the wheels" of the labor market by moving into the most favorable local labor markets. Within a spatial equilibrium framework, this means that they pick cities where wages are highest relative to living costs and amenity levels. Thus, in this context, immigrants do not necessarily choose the most productive cities, or those with the highest nominal wages. Instead, in our model, migrants prefer high-nominal-income cities because they care less than natives about local prices. This is a crucial difference that has important consequences for both the distribution of economic activity across space and the general equilibrium. Moreover, this insight also has important implications for empirical studies on immigration's effects on the labor market that rely on comparing metropolitan areas (see, among others, Card (1990), Altonji and Card (1991), Borjas et al. (1997), Card (2005), Lewis (2012), Llull (2017), Glitz (2012), Borjas and Monras (2017), Monras (2015b), Dustmann et al. (2017), Jaeger et al. (2018)).[12] In particular, it provides a strong explanation for why there is a positive correlation between wage levels and immigrant shares across metropolitan areas.

This paper is also related to a large body of recent work. Recent developments in quantitative spatial equilibrium models include Redding and Sturm (2008), Ahlfeldt et al. (2015), Redding (2014), Albouy (2009), Fajgelbaum et al. (2016), Notowidigdo (2013), Diamond (2015), Monras (2015a), Caliendo et al. (2015), Caliendo et al. (2017), and Monte et al. (2015), among others, and have been used to explore neighborhoods within cities, the spatial consequences of taxation, local shocks, endogenous amenities, the

[9] Large, expensive cities are so, in the context of our model, because they are more productive. See Albouy (2016). In related work Hsieh and Moretti (2017), show how housing constraints are responsible in part for the smaller than optimal size of the most productive cities. This paper shows that immigrant location choices reduce these constraints. On optimal city size see also Eeckhout and Guner (2014).

[10] This estimate depends, to some extent, on the agglomeration forces assumed in the model.

[11] There are other papers with models that help to make arguments similar to the one made in Borjas (2001), for example, Bartel (1989) and Jaeger (2007).

[12] Dustmann et al. (2016) provide a recent review of this literature.

dynamics of internal migration, international trade shocks, and commuting patterns.[13] However, only Monras (2015b), Piyapromdee (2017), and more recently Burstein et al. (2018), use a spatial equilibrium model to study immigration. Relative to these papers, we uncover novel facts that we use to understand general equilibrium effects of immigration that were unexplored until now. In fact, much of the literature on immigration ignores general equilibrium effects. Many studies in this literature compare different local labor markets–some that receive immigrants and some that do not (see Card (2001))–or different skill groups (see Borjas (2003)). Neither of these papers, nor the numerous ones that followed them, are well suited to exploring the general equilibrium effects of immigration, and only a handful of papers use cross-country data to speak to some of those effects (see, for example, Di Giovanni et al. (2015)). Within-country general equilibrium effects are, thus, completely under-explored in the immigration literature.

Finally, this paper also ties in with a significant amount of literature that investigates the effects of migrants on housing markets and local prices more generally. There is evidence that suggests that Hispanic migrants tend to settle in expensive metropolitan areas and that they exert pressure on housing prices (see Saiz (2003), Saiz (2007), and Saiz and Wachter (2011)). Relative to these papers, we document broader patterns in the data that are in line with this evidence and we provide a mechanism that can account for these facts and a quantitative spatial equilibrium model that highlights its importance. There is also some literature showing that immigration affects local prices (Lach, 2007; Cortes, 2008). This literature shows that price levels in high-immigrant locations may decrease relative to low-immigrant locations. This is usually explained by the impact that immigration has on the cost of producing some local goods. We abstract from this mechanism in this paper, but we could easily integrate it into the model and the results would be similar.

In what follows, we first describe our data. We then introduce a number of facts describing immigrants' residential choices, incomes, and consumption patterns. In Section 4, we build a model that rationalizes these facts. We estimate this model in Section 5, and we use these estimates to study the contribution of immigration to the spatial distribution of economic activity.

2 Data

For this paper, we rely on various publicly available data sets for the United States. For labor-market variables, we mainly use the US Censuses, the American Community Survey (ACS), and the Current Population Survey (CPS), all available on Ruggles et al. (2016) and widely used in previous work. For consumption, we combine a number of data sets that allow us to (partially) distinguish between natives' and immigrants' consumption patterns. These include the New Immigrant Survey and the Consumption Expenditure Survey. For country of origin data we use price levels estimated by the World Bank.[14] We describe these various data sets below.

[13] Redding and Rossi-Hansberg (Forthcoming) provide a recent review of this literature.

[14] We have also used per capita GDP from the Penn World Tables to check that our results are robust to using GDP per capita instead of price indices in the home country.

2.1 Census, American Community Survey, and Current Population Survey data

First, we use CPS data to compute immigrant shares, city size, and average (composition-adjusted) wages at high frequency. The CPS data are gathered monthly, but the March files contain more detailed information on yearly incomes, country of birth, and other variables that we need. Thus, we use the March supplements of the CPS to construct yearly data. In particular, we use information on the current location–mainly metropolitan areas–in which the surveyed individual resides, the wage they received in the preceding year, the number of weeks that they worked in the preceding year, and their country of birth. We define immigrants as individuals born outside the United States with no American parents. This information is only available after 1994, and so we only use CPS data for the period 1994-2011. To construct composition-adjusted wages, we use Mincerian wage regressions where we include racial categories, marital status categories, four age categories, four educational categories, and occupation and metropolitan-area fixed effects. The four education categories are: high school dropouts, high school graduates, some college, and college graduation or more.

Second, we use the Census of population data for the years 1980, 1990, and 2000. These data are very similar to the CPS, except that the sample size is significantly larger–from a few tens of thousands of observations to a few million observations. After 2000, the US Census data are substituted on Ipums by the ACS. The ACS contains metropolitan-area information only after 2005 and so we use these data. Again, the structure of these data is very similar to the Census and CPS data. Our treatment of the variables is identical in each case.

We also use these data to compute local price indices. To do this, we follow Moretti (2013) and apply his code to ACS and Census data. From that, we obtain a local price index for each of the metropolitan areas in our sample. The CPS does not contain a number of variables that are used for this computation–particularly housing price information–which explains why we cannot compute local price indices using CPS data.

To give a sense of the metropolitan areas driving most of the variation in our analysis, Table 1 reports the metropolitan areas with the highest immigrant share in the United States in 2000, together with some of the main economic variables used in the analysis. As we can see in Table 1, most of the metropolitan areas with high levels of immigration are also large and expensive and pay high wages. The gap in earnings between natives and immigrants is also large in these cities. In this general description, there are a few notable outliers, which are mostly metropolitan areas in California and Texas relatively close to the US-Mexico border.

2.2 New Immigrant Survey and Consumer Expenditure Survey data

To explore whether immigrants consume less locally than natives, we employ a number of different data sets. First, we use data from the New Immigrant Survey to document remittance behavior. While not a large data set, it is the only one to our knowledge that provides information on both the income and the amount remitted at the individual or household level for immigrants residing in the US.

Table 1: List of top US cities by immigrant share in 2000

MSA	*Immig. (%)*	*Size rank*	*Population*	*Weekly wage*	*Price index*	*Wage gap (%)*
Miami-Hialeah, FL	64	23	1,056,504	332	1.13	-20
Los Angeles-Long Beach, CA	48	2	6,003,886	395	1.20	-24
McAllen-Edinburg-Pharr-Mission, TX	44	88	229,812	258	0.88	-16
San Jose, CA	44	25	888,632	563	1.52	-8
Salinas-Sea Side-Monterey, CA	40	146	120,699	355	1.22	0
El Paso, TX	40	70	291,665	300	0.92	-14
Brownsville-Harlingen-San Benito, TX	38	134	137,429	275	0.90	-17
New York, NY-Northeastern NJ	36	1	8,552,276	454	1.22	-19
Visalia-Tulare-Porterville, CA	33	125	155,595	306	0.95	-7
San Francisco-Oakland-Vallejo, CA	33	6	2,417,558	494	1.38	-10
Fort Lauderdale-Hollywood-Pompano Beach, FL	33	28	799,040	393	1.17	-12
Fresno, CA	30	56	396,336	327	0.98	-8
San Diego, CA	29	15	1,306,175	411	1.19	-13
Santa Barbara-Santa Maria-Lompoc, CA	29	112	176,133	390	1.25	-8
Riverside-San Bernardino, CA	28	14	1,428,397	388	1.07	-11
Ventura-Oxnard-Simi Valley, CA	28	61	362,488	460	1.23	-17
Stockton, CA	27	83	246,980	386	1.04	-14
Houston-Brazoria, TX	26	8	2,191,391	427	1.04	-18
Honolulu, HI	26	55	397,469	393	1.23	-4
Modesto, CA	25	102	203,134	372	1.03	-3

Notes: These statistics are based on the sample of prime-age workers (25-59) from the Census 2000. Weekly wages are computed from yearly wage income and weeks worked. Local price indices are computed following Moretti (2013). The wage gap is the gap in earnings between natives and immigrants, controlling for observable characteristics.

The second data set that we use is the Consumer Expenditure Survey, which is maintained by the Bureau of Labor Statistics and has been widely employed to document consumption behavior in the US. 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, which is why it is impossible to directly identify immigrants. Instead, we rely on one of the Hispanic categories that identifies households of Mexican origin in the years 2003 to 2015. The data set contains around 30,000 households per year, of which around 7 percent are of Mexican origin.

2.3 Origin country price index data

The World Bank provides price indices of a large number of countries in the world relative to the United States in its International Comparison Program database from 1990.[15] These data expand the 89 countries of origin that we use in our estimation exercise.[16]

3 Stylized facts

In this section, we start by documenting a series of facts about immigrants' location choices and wages. In particular, we show that immigrants concentrate much more than natives in large, expensive cities and that they tend to earn less than natives there. We also demonstrate that these patterns are stronger

[15] The exact title of the series is "Price level ratio of PPP conversion factor (GDP) to market exchange rate".

[16] An alternative source of similar information is provided by the OECD and the Penn World Tables. The OECD also estimates price levels of various countries. The number of countries that the OECD covers is smaller, which is why we report estimates in the paper using the World Bank data, although estimates for OECD countries may be more reliable. We obtain similar estimates using OECD data. We also obtain similar estimates using the GDP per capita in the country of origin, obtained from the Penn World Tables, to proxy for the price index.

for immigrants coming from lower-income countries, and, within Mexican immigrants, for immigrants who moved to the US in high exchange-rate years. In the second part of this section, we document immigrants' consumption behavior, showing that immigrants tend to consume less than similar-looking natives at the local level.

3.1 Cities, labor market outcomes, and immigrants

3.1.1 Immigrants' location choices and city size

The first fact that we document in this paper is that immigrants tend to live in larger, more expensive cities in greater proportions than natives. This is something that was known to some extent in the literature (see, for example, Eeckhout et al. (2014) and Davis and Dingel (2012)), but here we document it much more systematically: we use a much larger number of data sets and we expand the existing literature by showing that there is also a strong relationship between immigrant shares and local price indices.

A simple way to document this fact is to regress the distribution of immigrants relative to the distribution of natives on city size or price level. In order to do this, we define the relative immigrant distribution as the share of immigrants living in city c divided by the share of natives living in city c and regress this measure (in logs) on the size or price level of city c. More specifically, we run the following regression:

$$\ln\left(\frac{\mathrm{Imm}_{c,t}}{\mathrm{Imm}_t}/\frac{\mathrm{Nat}_{c,t}}{\mathrm{Nat}_t}\right) = \alpha_t + \beta_t \ln P_{c,t} + \varepsilon_{c,t}, \tag{3.1}$$

where $\mathrm{Imm}_{c,t}$ is the number of immigrants and $\mathrm{Nat}_{c,t}$ is the number of natives in city c at time t. When the subscript c is omitted, the variables represent the total number of immigrants or natives living in cities in a particular time period. $P_{c,t}$ is either the total number of people in the city or its price level. We run separate regressions for each year.

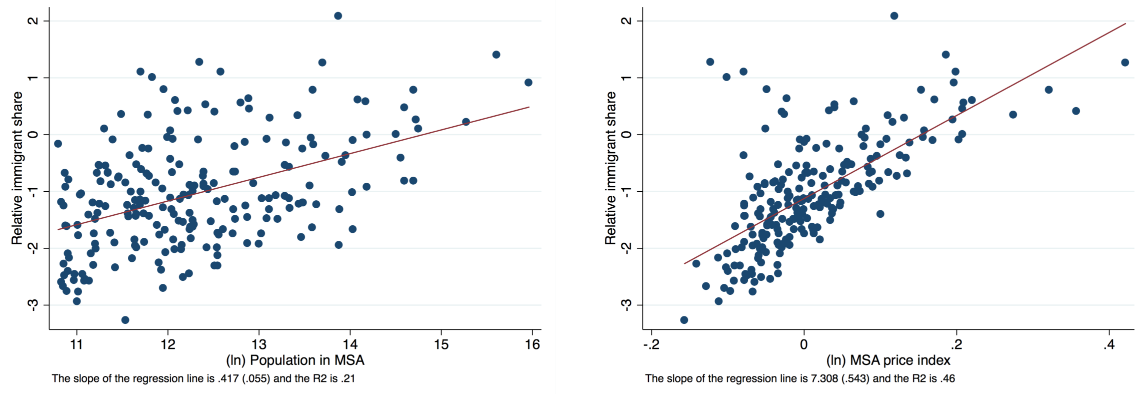
Figure 1 shows these relationships using data from the Census 2000. In the left-hand panel, we observe that, even if there is some variance in the immigrant distribution across metropolitan areas, there is a clear positive relationship between immigrants and city size. This relationship is statistically significant. The relationship between immigrant share and price indices is even stronger and the linear fit better, as shown in the right-hand panel of Figure 1.[17] While there are some exceptions, mainly along the US-Mexico border, a city with a local price index that is 1 percent higher is associated with an increase of around 7 percent in the relative immigrant share as measured by the left-hand variable in Equation 3.1. In Appendix B.4, we show that this relationship between the population level and the relative immigrant share also holds when using commuting zones instead of metropolitan areas.

In Figure 2, we investigate how these relationships have evolved over time. To show this, we first run a linear regression following Equation 3.1 for each of the years displayed along the x-axis of the figure against the city size or the price index, and we then plot the various estimates and confidence intervals for these elasticities.

The left-hand panel in Figure 2 shows that the relationship between the relative immigrant share

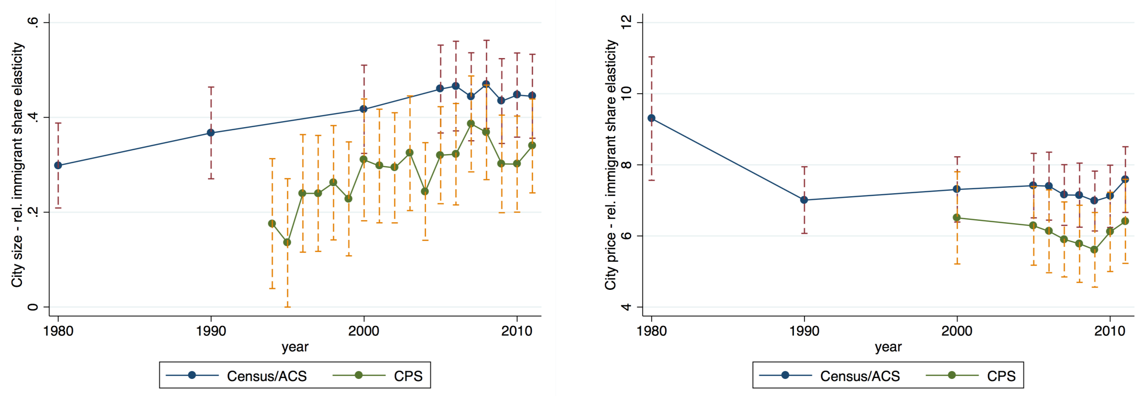
[17] This is also the case when we include both city price and city size in a bivariate regression.

Figure 1: City size, price index, and relative immigrant share



Notes: The figure is based on the sample of prime-age workers (25-59) from the Census 2000. The MSA price indices are computed following Moretti (2013). Each dot represents a different MSA. There are 219 different metropolitan areas in our sample.

Figure 2: Evolution of the city size/price elasticity of the relative immigrant share



Notes: This figure uses Census/ACS and CPS data from 1980 to 2011 to estimate the relationship between the share of immigrants among all US immigrants relative to the share of natives among all US natives living in a city and its size and price. price indices can only be computed when Census/ACS data are available. Each dot represents the corresponding estimate of the elasticity of the relative immigrant distribution, city size, and city prices for each corresponding year. Vertical lines represent 95 percent confidence intervals.

and city size has been positive since the 1980s. This relationship has become slightly stronger over time. While in 1980 the elasticity was around 0.3 percent, it has increased over the years to reach almost 0.5 percent when using the Census data. We observe a similar trend in the CPS data, but estimates are smaller and noisier, most likely because of measurement error. The elasticity of immigrant shares and local price indices first decreased from around 9 to 7 percent between 1980 and 1990 but has remained relatively stable since then.

We can summarize these two figures as follows:

Fact 1. *Immigrants concentrate in large, expensive cities much more than natives.*

3.1.2 Wages, city size, and local price indices

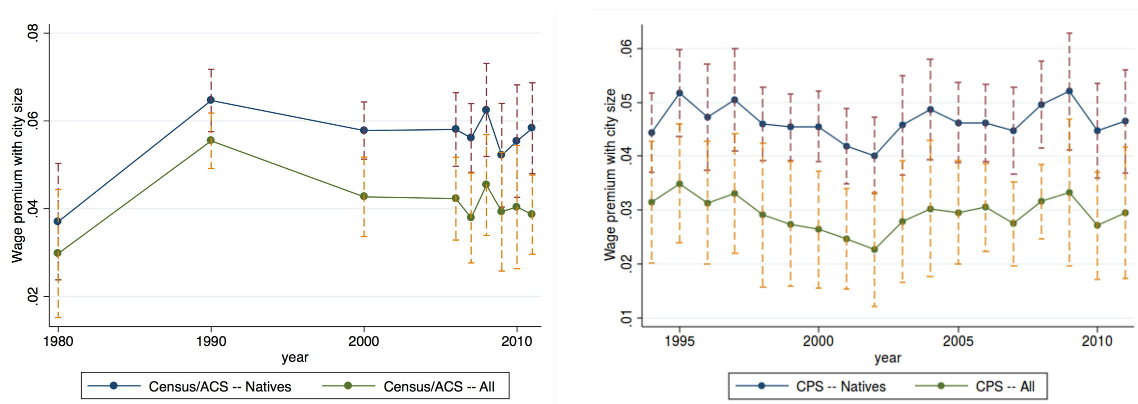
It is a well-known fact that wages are higher in larger cities (see, for example, Baum-Snow and Pavan (2012)). Moreover, this relationship has become stronger over time. In this section, we demonstrate this fact with our data. We show results using both the average (composition-adjusted) wages of natives alone and natives together with immigrants. To illustrate this fact, we again use various cross-sectional regressions and plot the estimates for each of the years. More specifically, we run regressions of the following type:

$$\ln w_{c,t} = \alpha_t + \beta_t \ln P_{c,t} + \varepsilon_{c,t} \tag{3.2}$$

where, as before, $P_{c,t}$ is either the total amount of people in the city or its price level and where $w_{c,t}$ is a measure of local wages.

In Figure 3, we show the evolution of the city size premium using Census data (left) and CPS data (right). We can compute this premium using natives and immigrants or focusing on native wages alone. In both cases, we always obtain positive and significant estimates. The city size wage premium has increased in the United States since 1980, although it has remained flat over the last 20 years or so (Baum-Snow and Pavan, 2012). Census estimates are slightly larger than CPS estimates–again, a consequence of measurement error in CPS data. A remarkable finding is that the city size premium is significantly smaller when combining both natives and immigrants for the computation of average (composition-adjusted) wages. We will come back to this point later.

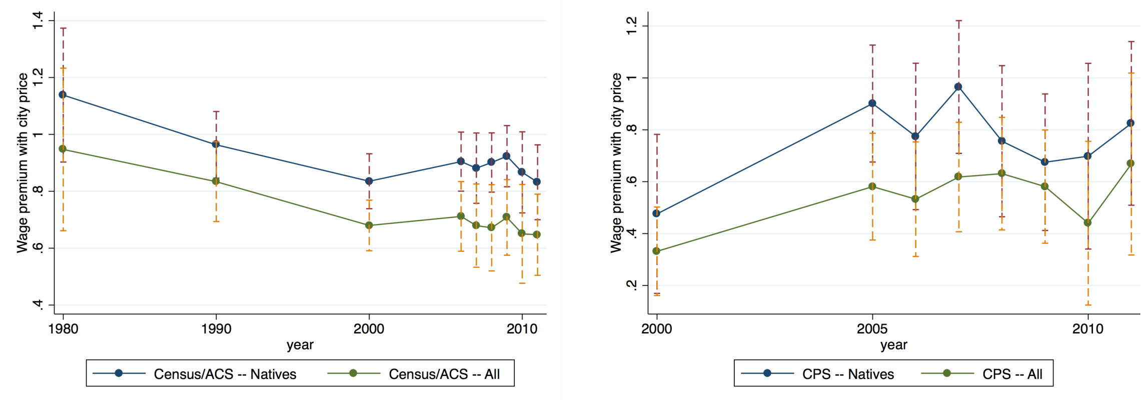
Figure 3: Evolution of city size premium



Notes: This figure uses Census/ACS and CPS data from 1980 to 2011 to estimate the relationship between wage levels and city size. Each dot represents the corresponding estimate of the elasticity of immigrant shares, city size, and city prices for each corresponding year. CPS data start reporting place of birth only in 1994. Vertical lines represent 95 percent confidence intervals.

In Figure 4, we repeat the exercise using price levels instead of city size. We obtain very similar patterns. The city price -wage premium is just less than 1. This means that an increase in the price level translates almost one for one to the wages paid in the city. If anything, this relationship has declined over the last 30 years or so. This is mainly due to the increase in price levels, as can be seen in Figure B.2 in the Appendix. Again, as was the case with the city size wage premium, when we also use immigrants

Figure 4: Evolution of city price level premium



Notes: This figure uses Census/ACS and CPS data from 1980 to 2011 to estimate the relationship between wage levels and city prices. price indices can only be computed when Census/ACS data are available. Each dot represents the corresponding estimate of the elasticity of immigrant share, city size, and city prices for each corresponding year. CPS data start reporting the place of birth only in 1994. Vertical lines represent 95 percent confidence intervals.

to compute it, we see that the relationship is weaker than if we only use natives. This is true both when we use ACS/Census data and when we use CPS data.

We can summarize this fact as:

Fact 2. *Wages are higher in larger, more expensive cities. Both the city size wage premium and the city price wage premium are higher when wages are computed using the native population only.*

3.1.3 Immigrant wage gaps

In Figures 3 and 4, we observe that the city size and city price premiums seem to be significantly smaller when using immigrants to compute average (composition-adjusted) wages. In this subsection, we investigate this further. To that end, we compute the gap in wages between natives and immigrants as a function of city size and city prices.

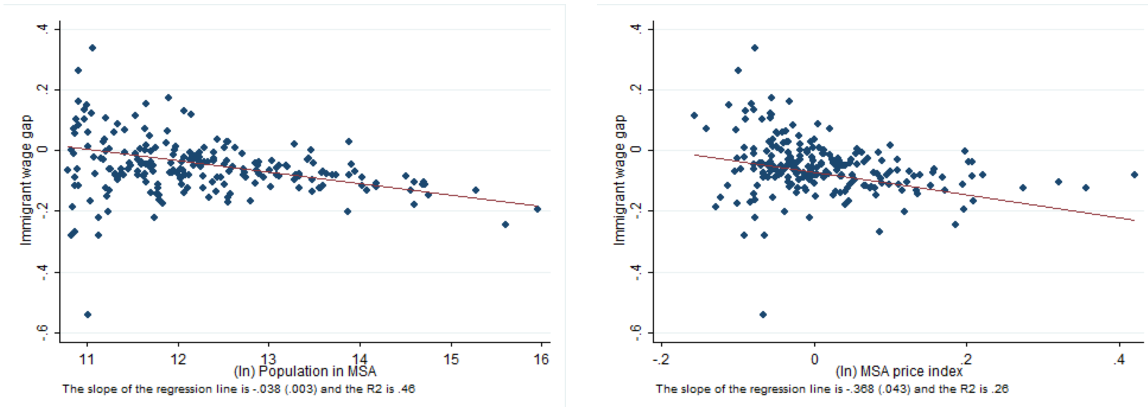
As before, we show the results in two steps. In Figure 5, we show the estimates using data from the Census 2000. In the left-hand panel, we plot the difference in wages between natives and immigrants in our sample of metropolitan areas against the size of these cities. The relationship is negative and strong. The estimate is -0.038, meaning that if a city is 10 percent larger, the gap in wages between natives and immigrants is 0.38 percent larger. Again, in Appendix B.4, we show that the relationship between the population level and the immigrant wage gap also holds when using commuting zones instead of MSAs.

Moreover, the relationship between native-immigrant wage gaps and city size is very tight. The R squared is around 0.46, and the standard errors of the estimate are small. In fact, this relationship is extremely robust in the data. We run regressions of the type:

$$\ln w_{i,c,t} = \alpha_{1t} + \alpha_2 Imm_{i,c,t} + \beta Imm_{i,c,t} * \ln P_{c,t} + \gamma \ln P_{c,t} + \phi X_{i,c,t} + \varepsilon_{i,c,t} \tag{3.3}$$

where i indexes individuals, c indexes cities, t indexes years, Imm is an indicator variable for i being an immigrant, $\ln P$ indicates city size or city prices, and X contains observable individual characteristics

Figure 5: City size, price index, and wage gaps



Notes: This figure uses data from the Census 2000 to show the relationship between native-immigrant wage gaps and city sizes and prices. Each dot represents the gap in earnings between natives and immigrants in a metropolitan area. The red line is the fitted line of a linear regression.

Figure 6: Evolution of the city size/price elasticity of the wage gap

Notes: This figure uses Census and CPS data from 1980 to 2011 to estimate the relationship between native-immigrant wage gaps and city size and prices for each year. Each dot represents an estimate of the native-immigrant wage gap elasticity with city size and the city price index. The vertical lines represent 95 percent confidence intervals.

as well as year and metropolitan ares (MSA) fixed effects.[18] In all our estimates, we obtain a negative β that remains highly statistically significant no matter what type of data or variation we use, as shown in Appendix C.[19]

One way to assess the stability of the relationship between native-immigrant wage gaps and city size over time is estimating the model for each year. The results are shown in Figure 6. As before, we show the estimates using both Census and CPS data over a number of years between 1980 and 2011. The relationship remains tight at around 0.035 through the entire period in both data sets. The right-hand

[18]The individual controls are five dummies for race (white, black, American Indian/Aleut/Eskimo, Asian/Pacific Islander, other), five for marital status (married, separated, divorced, widowed, never married/single), four age groups (three ten-year intervals from 25 to 54 and 55-59), four education categories (high school dropout, high school graduate, some college, college graduate or more), and 82 occupation categories, which are based on the grouping of the 1990 occupation codes from https://usa.ipums.org/usa/volii/occ1990.shtml.

[19]The regression results of the above baseline regression can be found in Table C.1.

panels of Figures 5 and 6 show the relationship between native-immigrant wage gaps and local price levels. We also observe a negative and tight negative relationship. If anything, it seems that over time, this relationship has become a little weaker, but remains at around -0.36.

To the best of our knowledge, this is the first paper to document this very strong feature of the data in the United States. It suggests that, for whatever reason, immigrants that live in larger, more expensive cities are paid less relative to natives than immigrants that live in smaller, less expensive cities.[20] This is not driven by immigrant legal status. In Appendix B.3, we show that we obtain a similar relationship for documented and undocumented immigrants.[21] Nor is this driven by the composition of immigrants across US cities. In Figures 5 and 6, we control for observable characteristics, which include education, race, marital status, and occupation, etc. Furthermore, we check that this relationship prevails for each education group independently by running separate regressions by education category, and that it is robust to controlling for immigrant networks and for imperfect native-immigrant substitutability, as reported in Appendix B.1.

We can summarize this fact as follows:

Fact 3. *The gap in wages between immigrants and natives increases with city size. Over time, this gap has been stable.*

3.1.4 Immigrant heterogeneity

Later in the model section, we argue that the results reported so far can be explained by the fact that part of what immigrants consume is related to home-country price indices instead of local ones. This implies that, if there is some degree of substitution between consuming locally or consuming in the country of origin, the patterns documented so far should be stronger for immigrants coming from countries of origin with lower price indices.

To show that this is indeed the case, we carry out two alternative exercises in this subsection. First, we show that the relationships between relative location choices, wage gaps, and local price indices are stronger for immigrants coming from lower home-country price indices. We use both across and within country variation to document this fact. Second, we use arguably exogenous exchange rate fluctuations between Mexico and the US to show that these patterns are stronger for Mexicans that migrate to the US when the price of the Mexican peso is low relative to the dollar.

We also show in this section that the patterns in relative wages between immigrants and natives are stronger for Mexicans living closer to the border. We argue that this is in line with the idea that Mexicans closer to the border may have tighter ties to their country of origin.

All this evidence, together with the consumption patterns documented in Section 3.2, is key to highlighting the mechanism that generates a differential distribution of immigrants and natives across locations, as emphasized in the model that we introduce in Section 4.

Heterogeneity by country-of-origin price index

[20] On average, immigrants earn less than natives, but this is driven mostly by immigrant wages from lower-income countries and by immigrants of all income levels in larger cities.

[21] To identify likely undocumented immigrants in the Census data, we apply the method described in Borjas (Forthcoming).

Our main hypothesis is that the relationships described in Facts 1 to 3 emerge because immigrants have more incentives than natives to live in large, more expensive cities that pay, on average, higher nominal wages if consumption in their home country is cheaper than local consumption. To explore whether the data are in line with this hypothesis, we rely on immigrant heterogeneity: some immigrants come from rich countries, with price levels similar to the ones in the US, which gives them fewer incentives to consume in their home countries. This should result in a flatter relationship between relative immigrant shares and immigrant-native wage gaps for immigrants coming from countries of origin with higher price levels. To explore this possibility we expand equations 3.1 and 3.3 as follows:

$$\ln(1+\frac{\mathrm{Imm}_{c,o,t}}{\mathrm{Imm}_{o,t}}/\frac{\mathrm{Nat}_{c,t}}{\mathrm{Nat}_{t}}) = \alpha_1 \ln P_{c,t} + \alpha_2 \ln P_{o,t} + \alpha_3 \ln P_{c,t} * \ln P_{o,t} + \delta_t + (\delta_o + \delta_c) + \varepsilon_{c,t} \tag{3.4}$$

$$\ln w_{i,c,t} = \beta_1 \ln P_{c,t} + \beta_2 \ln P_{o,t} + \beta_3 \ln P_{c,t} * \ln P_{o,t} + \delta_t + (\delta_o + \delta_c) + \phi X_{i,c,t} + \varepsilon_{i,c,t} \tag{3.5}$$

where as before $\ln P_{c,t}$ denotes the population or the price level of metropolitan area c, and where $\ln P_{o,t}$ denotes the price level of country of origin o relative to the US. It is is worth noting that we use $\ln(1+\frac{\mathrm{Imm}_{c,o,t}}{\mathrm{Imm}_{o,t}}/\frac{\mathrm{Nat}_{c,t}}{\mathrm{Nat}_{t}})$ instead of $\ln(\frac{\mathrm{Imm}_{c,o,t}}{\mathrm{Imm}_{o,t}}/\frac{\mathrm{Nat}_{c,t}}{\mathrm{Nat}_{t}})$ because this exercise is quite demanding in terms of data, and, thus, there are a few zeros. To avoid measurement error problems, we also restrict these regressions to the top 100 metropolitan areas in terms of size.[22]

In the wage regressions, $\ln P_{o,t}$ takes value 0 for individuals i that are born in the US. Thus, this is a difference-in-difference specification that captures the heterogeneity of our results with respect to the country of origin. The estimate of interest are α_3 and β_3. A negative estimate of α_3 means that when the price level of origin is lower, immigrants from this country of origin tend to concentrate more in larger, more expensive metropolitan. Similarly, a positive estimate of β_3 implies that the wage gaps of immigrants from these countries relative to natives are larger in these larger, more expensive metropolitan areas.

It is worth noting that we can estimate these equations using two different sources of variation. If we include country of origin fixed effects, α_3 and β_3 are identified through changes in the price level at origin across different years. If we do not include country of origin fixed effects, α_3 and β_3 are identified by comparing different countries of origin across metropolitan areas.

We present the results in Table 2, where we report only selected coefficients. Panel A show the results of estimating how relative immigrant shares change with the interaction of local sizes and prices with the price level of the country of origin while panel B repeats the exercise for wages. Columns (1) and (2) use across country of origin variation, while columns (3) and (4) use within country of origin variation. The results are clear. When price levels in the country of origin are low, immigrants tend to concentrate much more in larger metropolitan areas and they tend to receive lower wages. Moreover, the results

[22] Different selections of metropolitan areas lead to slightly different selections on the number of sending countries which result in small changes in the estimates. Expanding the number of metropolitan areas tends to introduce more measurement error. This tends to attenuate the estimates of the regressions with many fixed effects, something that is a normal consequence of estimating many fixed effects with measurement error. Reducing the number of metropolitan areas obviously reduces the number of observations which has small consequences on the point estimates and confidence intervals.

Table 2: Immigrant Heterogeneity

Panel A: Location choices

	(1)	(2)	(3)	(4)
	Rel. Imm. share	Rel. Imm. share	Rel. Imm. share	Rel. Imm. share
VARIABLES	OLS	OLS	OLS	OLS
(ln) Population in MSA x (ln) Real xrate	-0.0418**		-0.0434***	
	(0.0207)		(0.0168)	
(ln) City price x (ln) Real xrate		-0.0326		-0.0461*
		(0.0309)		(0.0264)
Observations	26,700	26,700	26,700	26,700
R-squared	0.112	0.148	0.380	0.379
Year FE	yes	yes	yes	yes
MSA FE	no	no	yes	yes
Country origin FE	no	no	yes	yes

Panel B: Wage gaps

	(1)	(2)	(3)	(4)
	(ln) Wage	(ln) Wage	(ln) Wage	(ln) Wage
VARIABLES	OLS	OLS	OLS	OLS
(ln) Population in MSA x (ln) Real xrate	0.0531***		0.0485***	
	(0.0104)		(0.00393)	
(ln) City price x (ln) Real xrate		0.0491**		0.0431**
		(0.0236)		(0.0173)
Observations	3,083,257	3,083,257	3,083,257	3,083,257
R-squared	0.379	0.380	0.391	0.390
Xs	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
MSA FE	no	no	yes	yes
Country origin FE	no	no	yes	yes

Notes: This table shows regressions of relative immigrant shares and wages on population/city prices, exchange rates and the interaction between these two variables. A number of controls are added across columns. The regressions are limited to the top 100 metropolitan areas in size and 89 sending countries for the years 1990, 2000, and 2010. Standard errors clustered at the metropolitan area - country of origin level are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.

do not depend on the type of variation that we use to estimate the heterogeneity of immigrant location choices and their wages and how this varies with city sizes and local price levels.

Heterogeneity within Mexican immigrants: real exchange rate fluctuations

To provide further evidence for our hypothesis, we use in this section high frequency fluctuations in real exchange rates. Exchange rate fluctuations are common and difficult to anticipate over short time horizons. Variation in exchange rates is likely to be a source of exogenous variation that can inform whether immigrants decide differently on their location choices as a function of price indices at origin and destination.[23]

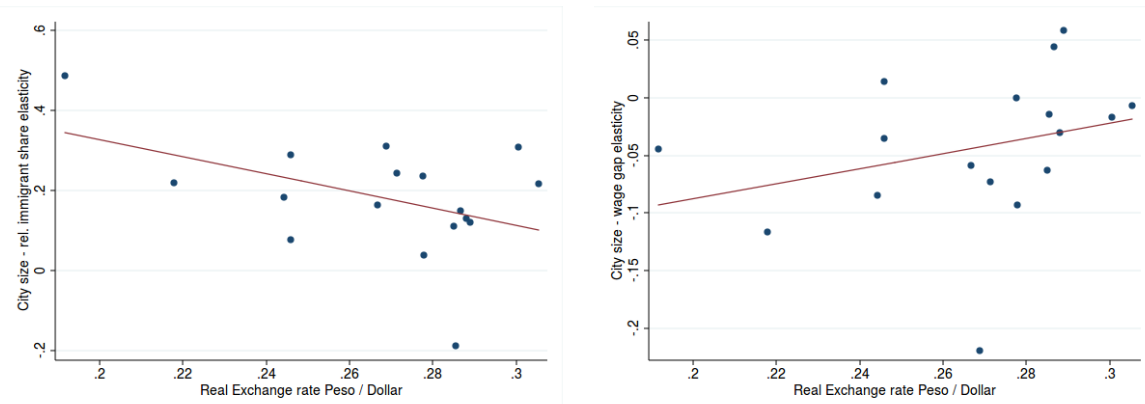
More concretely, we focus our analysis on migrants who change residences in a given year. We investigate whether these immigrant movers decide to concentrate more in large cities in years when prices in their home country are lower. For this exercise, we need the longest possible series of yearly

[23]In this paper, we complement the evidence shown in Nekoei (2013). Exchange rate fluctuations affect not only the intensive margin of immigrant labor supply decisions (i.e. hours worked) but also, and very importantly, the extensive margin (i.e. location choices).

data on a group of immigrants. For this reason, we use CPS data and concentrate on Mexican migrants: Mexicans are the largest immigrant group, and thus measurement error is likely smaller for this group.

Intuitively, the higher the real exchange rate between the dollar and the currency of the country of origin, in our case Mexico, the cheaper consumption at home is for immigrants. Given these cheaper home-country prices, immigrants have a greater incentive to live in large, expensive cities with high nominal wages and are willing to accept relatively lower wages in these locations. Thus, when home-country prices are lower, the elasticities of the relative immigrant share and the wage gap should be higher (in absolute terms).

Figure 7: City size elasticity of relative immigrant share and wage gap of Mexicans



Notes: This figure uses data from the CPS 1994-2011 to show the relationships between the city size elasticity of the relative immigrant share and the wage gap of Mexican immigrants that changed location during the year preceding the survey. We estimate the elasticity for each year and plot it against the average real exchange rate of the Mexican peso to the US dollar during that year. Each dot represents an estimate of the coefficient β for the particular year based on Equations 3.1 and 3.3.

We estimate Equations 3.1 and 3.3 using Mexican movers separately for each year and plot the β coefficients against the average real exchange rate of the Mexican peso to the US dollar during that year.[24] The two plots in Figure 7 show a linear fit that goes in the expected direction. The lower the prices in Mexico relative to the US, the more positive the elasticity of the relative share of Mexican immigrants and the more negative the elasticity of the wage gap with respect to city size. Note that the largest shock to the real exchange rate happened in 1995, which is the outmost point on the left, and persisted into 1996, whereas the rate was relatively stable at around .28 during the 2000s. Certainly, the small fluctuations in these years would go unnoticed for most Mexicans and therefore we see no clear pattern in the plots around this value. However, the significant depreciation of the Mexican peso at the end of 1994 was clearly an event of which many Mexicans were aware. Thus, the fact that the elasticities are especially high in 1995 and 1996 supports our notion that the relative affordability of home consumption influences immigrants' residential choices by changing their incentives to live in cities with high nominal wages.

Heterogeneity within Mexican immigrants: distance to the border

[24] We do not take the log of the left-hand side of Equation 3.1 to avoid losing MSAs without Mexican immigrant movers. Further, the place of residence in the previous year is not available for the survey year of 1995. Thus, we cannot use the wage year of 1994 for our estimates.

An alternative source of heterogeneity is potentially provided by Mexicans who live closer to or further away from the border. The former are likely to have stronger ties to Mexico. These ties may take various forms. When living closer to the border, it may be easier to spend longer periods of time in Mexico and to stay in closer touch with family members not in the United States, and thus the weight of their home country may be greater. We can use this insight to see whether the wage gap between Mexicans and natives, and the relationship between this gap and city size, is stronger for Mexicans close to the border.[25] For this, we run the wage regressions with Mexican immigrants separately for people living in cities in border states and for people living in non-border states. In order to account for characteristics of Mexicans that might differ across these samples and are likely to influence wages, we include years in the US and a dummy for being undocumented as additional controls.

Table 3: Mexican-native wage gaps and distance to Mexico

	Panel A			
	(1)	(2)	(3)	(4)
	Wage	Wage	Wage	Wage
	All workers	All workers	Low-skilled	Low-skilled
VARIABLES	OLS	OLS	OLS	OLS
Immigrant	-0.405***	-0.261***	-0.402***	-0.282***
(Mexican immigrants only)	(0.0417)	(0.0221)	(0.0400)	(0.0310)
Sample	Border states	Non-border states	Border states	Non-border states
Observations	62,784	245,634	28,375	91,648
R-squared	0.447	0.398	0.323	0.287

	Panel B			
	(1)	(2)	(3)	(4)
	Wage	Wage	Wage	Wage
	All workers	All workers	Low-skilled	Low-skilled
VARIABLES	OLS	OLS	OLS	OLS
(ln) Population in MSA	0.0274	0.0347**	0.0275	0.0166
	(0.0249)	(0.0143)	(0.0323)	(0.0236)
(ln) Population in MSA x Immigrant	-0.0410***	-0.0322***	-0.0303***	-0.0265***
(Mexican immigrants only)	(0.00797)	(0.00989)	(0.00875)	(0.00800)
Sample	Border states	Non-border states	Border states	Non-border states
Observations	62,784	245,634	28,375	91,648
R-squared	0.448	0.398	0.324	0.288

Notes: These regressions report only selected coefficients. The complete set of explanatory variables is specified in Equation 3.3, and is expanded by including the years that Mexicans have been in the US and a dummy for likely undocumented status (based on Borjas (2017)). Metropolitan-area fixed effects and year fixed effects are also included in the regression. These regressions use CPS data for the years 1994-2011. Low-skilled is defined as having a college degree or less. Robust standard errors, clustered at the metropolitan area level, are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.

Panel A in Table 3 shows that Mexicans close to the Mexican border earn less relative to natives than Mexicans further away. Importantly, this relationship emerges even when we control for the number of years that Mexicans have been in the US and both when comparing Mexicans of all education groups to natives (Columns 1 and 2) and when concentrating on the sample of low-skilled workers (Columns 3 and 4). This could suggest that, given that a larger part of the consumption of Mexicans close to the border is likely to be related to prices in Mexico, this allows Mexicans close to the border to accept lower wages. There are also alternative explanations for these results, so it is worth emphasizing that we take them

[25] Cities close to the Mexican border are defined as locations in California, Arizona, New Mexico, or Texas, which are the four states that share a border with Mexico.

Table 4: Remittances

Origin region	*Frequency (%)*	*Income share (%)*	*Income share for remit>0 (%)*
Latin America	32.54	2.35	8.86
Africa	30.31	2.57	12.17
Asia	25.31	2.81	12.8
Mexico	20.55	2.57	14.02
Europe	12.93	1.25	10.73
Total	24.73	2.24	10.98

Notes: These data come from the 2003 NIS, a representative sample of newly admitted legal permanent residents. Statistics are based on a subsample of immigrants with positive income (from wages, self-employment, assets, or real estate) and with a close relative (parent, spouse, or child) living in the country of origin. Income shares over 200% are dropped.

purely as suggestive evidence that the mechanism posited in this paper may be relevant for explaining these patterns in the wages of immigrants of the same country of origin.

Panel B in Table 3 shows that the gap in wages between Mexicans and natives decreases faster with city size in locations close to the Mexican border than in locations further away. This relationship is what we use in Section 5 to estimate the model and obtain the importance of the home country in host-country local consumption. It suggests, thus, not only that Mexicans earn less closer to the border than further away (Panel A), but also that the relationship between Mexican-native wage gaps and city size is stronger closer to the border than further away (Panel B).[26]

3.2 Immigrant consumption and return migration patterns

In this paper, we argue that one way to explain the distribution of immigrants across US cities and their wages relative to natives is that immigrants spend a part of their income in their host country. In this section, we show this importance of the home country by analyzing remittance behavior, housing expenditure, consumption expenditure, and return migration patterns. All of these are in line with the notion that part of the consumption of immigrants takes place in the country of origin.

3.2.1 Remittances

Dustmann and Mestres (2010) report that immigrants in Germany remit around 10 percent of their income. While data of the same quality do not exist for the US, we can use the New Immigrant Survey to document the remittance behavior of immigrants in the US. Table 4 reports the frequency, the share of income, and the share of income for those immigrants that remit for a number of different origins. There is quite some variation in the frequency of remitting across origins. For example, 20 percent of immigrants from Mexico and as much as 32 percent of immigrants from other Latin American countries seem to remit part of their income to their home countries. This number is significantly lower for immigrants from European countries.

For the entire population of immigrants, immigrant remittances represent approximately between 2

[26]We carried out a similar exercise comparing large and small Mexican households to see whether these patterns are also stronger for smaller Mexican households, which are presumably more attached to Mexico, than for larger ones. The results indicate that this is indeed the case, in line with the idea of this paper.

and 3 percent of income. For those who remit, this number logically increases to between 10 and 15 percent, which is closer to the estimate provided in Dustmann and Mestres (2010). All in all, the numbers for the US seem broadly consistent with this prior literature. The main drawback of New Immigrant Survey data is that it does not include undocumented immigrants. Including them would likely change the numbers significantly.

3.2.2 Expenditure on housing

One way to explore whether immigrants consume different local goods than natives is to investigate housing expenditure. If immigrants spend a portion of their income on home goods, they should (potentially) spend a lower share of their income on housing. This could be seen both in ownership rates and in rental prices paid.

First, if immigrants plan on returning home it is likely that ownership rates are lower among them. Ownership rates vary considerably by income and other characteristics. Thus, it may be useful to see if it is indeed the case that homeownership rates are lower among immigrants than *similar-looking* natives. This can be shown with the following regression:

$$\text{Owner}_i = \alpha + \beta \text{Immigrant}_i + \gamma \ln \text{Household Income}_i + \eta_c X_i + \varepsilon_i \tag{3.6}$$

where "Owner" indicates whether the head of household i is a homeowner or not, Immigrant_i is a dummy indicating that household i has at least one immigrant, and X_i denote various household characteristics, like the education level of the head of the household, marital status, the race of the head of the household, the size of the household, metropolitan-area fixed effects, occupation fixed effects, and time fixed effects. Thus, β identifies whether immigrants tend to rent rather than own the house in which they live relative to similar-looking natives.

The results are shown in Table 5, using Census and ACS data. It is apparent that immigrants are around 6 percentage points less likely to own the house in which they reside. This is true for a number of different subsamples. Column 1 uses only immigrant households where the head of the household works. Column 2 includes all households, irrespective of their labor-market status. Column 3 includes households in the bottom half of the income distribution. Column 4 investigates where there are significant differences in small relative to large cities, something that in this case does not seem to play an important role.

A second question is whether among renters immigrants consume less on local housing than similar-looking natives. Note that, again, differences in characteristics of the immigrant and native populations are going to translate into heterogeneity in housing expenditure that is not related to having a country of origin in which to consume. That is why it is important to control for personal characteristics and household income to make immigrants and natives "comparable". We use two alternative data sets to show that immigrants consume less on housing relative to "comparable", similar-looking natives.

The first piece of evidence comes from Census and ACS data, which can be used to compute "Monthly Rents" and total household income, and at the same time identify the country of birth of each individual. We can thus use the following regression equation:

Table 5: Immigrants' homeownership rates

VARIABLES	(1) Ownership OLS	(2) Ownership OLS	(3) Ownership OLS	(4) Ownership OLS
Immigrant	-0.0614***	-0.0624***	-0.0566***	-0.0539***
	(0.00567)	(0.00574)	(0.00648)	(0.00424)
(ln) Population in MSA x Immigrant				-0.000628
				(0.000465)
(ln) Population in MSA				0.00535
				(0.0116)
Total household income	0.175***	0.152***	0.121***	0.152***
	(0.00264)	(0.00220)	(0.00284)	(0.00219)
Observations	6,695,378	8,760,414	4,284,743	8,760,414
Sample	workers	all	income < p50	all
Controls	yes	yes	yes	yes

Notes: This table reports the regression of a homeownership dummy on an immigrant dummy and a number of observable characteristics as controls which include household income, race, occupation, metropolitan area of residence, family size, and marital status. Data from the US Census and ACS from 1980 to 2011 are used. Metropolitan-area and year fixed effects are included in all the regressions. Standard errors clustered at the metropolitan area level. One, two, and three stars denote 10, 5, and 1 percent significance levels respectively.

$$\ln \text{Monthly Rents}_i = \alpha + \beta \text{Immigrant}_i + \gamma \ln \text{Household Income}_i + \eta_c X_i + \varepsilon_i \tag{3.7}$$

to investigate whether households with at least one immigrant consume less than natives once we control for household income. When the income measure is continuous, we could instead use as dependent variable "Monthly Rent / Income", which should lead to similar results, as we show below.

A different type of data that contain housing expenditure is the Consumer Expenditure Survey. The main drawback of these data is that they do not allow us to identify the country of birth of each individual. Instead, we need to rely on the identification of Hispanics from Mexico (which should be highly correlated with Mexican-born individuals, which, in turn, is one of the main immigrant groups). In these data, moreover, we do not have a continuous measure of household income. Instead, we have nine different income categories that we can use in our estimation. In particular, we run regressions of the following type:

$$\ln \text{Housing Expenditure}_i = \alpha + \beta \text{Mexican}_i + \sum_j \gamma_j \text{Household Income category } j_i + \eta_c X_i + \varepsilon_i \tag{3.8}$$

where "Housing expenditure" is the reported expenditure on housing and "Mexican" identifies households of Mexican origin.

The results are reported in Panels A, B, and C in Table 6. In Panel A, we show that immigrants pay on average around 3 to 4 percent less in rental prices than similar-looking natives. In Column 1, we use the full sample of households where the head is working. Using this sample, we find that, once we control for personal characteristics and, very importantly, for household income, immigrant households pay monthly rents that are around 3 to 4 percent lower than native households. The estimates are similar when we

Table 6: Immigrants' expenditure on housing

Panel A: Census and ACS data

VARIABLES	(1) (ln) Monthly rent OLS	(2) (ln) Monthly rent OLS	(3) (ln) Monthly rent OLS	(4) (ln) Monthly rent OLS
Immigrant	-0.0379***	-0.0294**	-0.0258	-0.0235***
	(0.0125)	(0.0122)	(0.0164)	(0.00592)
(ln) Pop x Imm				-0.000434
				(0.00120)
(ln) Pop				0.0149
				(0.0364)
Total HH income	0.216***	0.271***	0.207***	0.271***
	(0.00491)	(0.00618)	(0.00496)	(0.00625)
Observations	2,060,237	2,697,707	1,939,684	2,697,707
Sample	workers	rent<income	income < p50	rent<income
Controls	yes	yes	yes	yes

Panel B: Census and ACS data, shares

VARIABLES	(1) Rent/Income OLS	(2) Rent/Income OLS	(3) Rent/Income OLS	(4) Rent/Income OLS
Immigrant	-0.0178***	-0.00856***	-0.0226***	-0.00555***
	(0.00390)	(0.00321)	(0.00687)	(0.00185)
(ln) Pop x Imm				-0.000220
				(0.000330)
(ln) Pop				0.00776
				(0.0100)
Total HH income	-0.279***	-0.218***	-0.410***	-0.218***
	(0.00181)	(0.00224)	(0.00332)	(0.00227)
Observations	2,060,237	2,697,707	1,939,684	2,697,707
Sample	workers	rent<income	income < p50	rent<income
Controls	yes	yes	yes	yes

Panel C: Consumption Expenditure Survey data

VARIABLES	(1) (ln) Housing Expenditure OLS	(2) (ln) Housing Expenditure OLS	(3) (ln) Housing Expenditure OLS	(4) (ln) Housing Expenditure OLS
Mexican	-0.222***	-0.012	-0.124***	-0.059***
	(0.009)	(0.008)	(0.010)	(0.009)
Observations	105,975	105,975	105,975	105,975
R-squared	0.006	0.184	0.218	0.278
Controls	none	income	pers. characteristics	all

Notes: Panels A and C in this table show regressions of (ln) monthly gross rents on an immigrant dummy, (ln) total household income and observable characteristics which include race, occupation, metropolitan area of residence, family size, and marital status. Panel B reports regressions of the share of income spent on monthly rents on the same controls. Year fixed effects are also included. Panel C uses household income bins fixed effects instead of a continuous measure of income. Panel B uses housing rents as a share of income as a dependent variable. The data for Panels A and B are taken from the US Census and ACS from 1980 to 2011. The data for Panel C are taken from the Consumer Expenditure Survey. Sample "all" uses all possible observations. Sample "workers" uses the observations where the head of the household is working. Sample "rent<income" restricts the sample to households whose total income is larger than the total rent (i.e. 12 times the monthly rent). Sample "income < p50" restricts the sample to workers in the bottom half of the earnings distribution (including homeowners and renters). Standard errors are clustered at the metropolitan area level in Panels A and B and at the state level in Panel C. One, two, and three stars denote 10, 5, and 1 percent significance levels respectively.

use all households in the sample or households in the bottom half of the income distribution. In Column 4, we investigate whether these results vary with the size of the city. As with homeownership rates, this does not appear to be the case. Panel B reports the exact same results but using house expenditure as a share of income instead of (log) total housing expenditure as a dependent variable. Unsurprisingly, the results are in line with Panel A. Immigrant households consume around 1 to 2 percentage points less of their income on rents than similar-looking natives.

Panel C reports the results using Consumer Expenditure Survey data. These data do not identify metropolitan area, so all comparisons are within state. In Column 1, we show the regression of housing expenditure on a dummy indicating whether the household is of Mexican origin. The unconditional regression shows that it is indeed the case that households of Mexican origin consume less on housing. This, however, could simply reflect that they tend to earn less, or that their observable characteristics–

like education or residential choices–are such that these types of household tend, on average, to consume less on housing. Column 2 controls for household income. This drops the estimate to a statistical zero. Column 3 shows that controlling for personal characteristics and for time and state fixed effects is important. Mexican-origin households tend to be systematically different than native households in terms of education, residential choices, marital status, and, most importantly, family size. When in Column 4 we control for both income and personal characteristics, we see that Mexican households consume less on housing than similar-looking native households, although the difference is not as large as the unconditional regression. This is our preferred estimate and aligns very well with the Census estimates. Given that we do not know the metropolitan area of residence, we cannot see whether households in larger metropolitan areas appear to consume differently in this data set or not.

3.2.3 Total expenditure

While it seems clear that immigrants spend less on housing than natives, it may be that they use this income on some other local goods, or rather that they save it for future consumption. To explore this, we can use the Consumption Expenditure Survey data and compare total local expenditure by Mexican households to that of all other households, following Panel C in Table 6.[27] More specifically, we can use the following specification:

$$\ln \text{Total Expenditure}_i = \alpha + \beta \text{Mexican}_i + \sum_j \gamma_j \text{Household Yearly Income category } j_i + \eta_c X_i + \varepsilon_i \quad (3.9)$$

where "Total Expenditure" is quarterly total expenditure at the household level, and where "Mexican" identifies Mexican households and where we also control for household income categories.

Table 7: Immigrants' total expenditure, Consumer Expenditure Survey

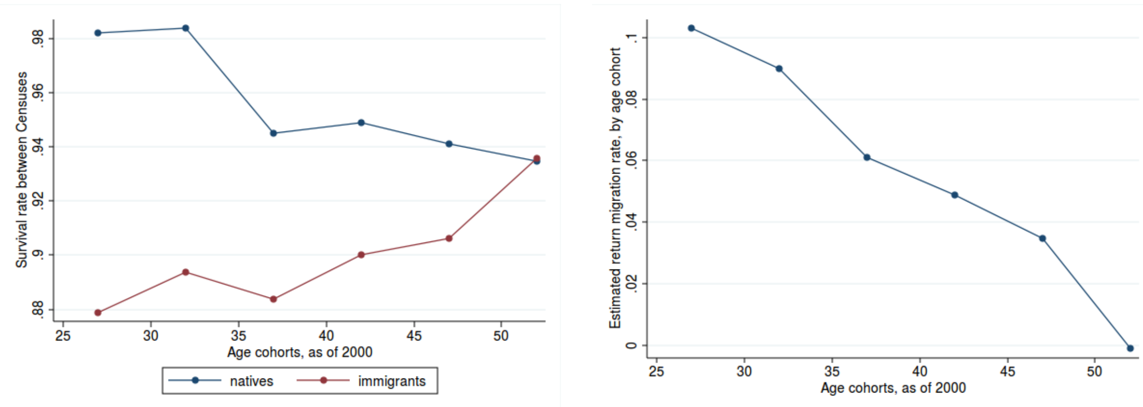
VARIABLES	(1) (ln) Total Expenditure OLS	(2) (ln) Total Expenditure OLS	(3) (ln) Total Expenditure OLS	(4) (ln) Total Expenditure OLS
Mexican	-0.325***	-0.091***	-0.198***	-0.115***
	(0.027)	(0.018)	(0.017)	(0.013)
Observations	105,975	105,975	105,975	105,975
R-squared	0.015	0.285	0.220	0.342
Controls	none	income	pers. characteristics	all

Notes: This table shows regressions of (ln) total expenditure on a number of personal characteristics and an indicator for Mexican households. This first column does not control for any observables. Column 2 controls for personal characteristics and time and state fixed effects. Columns 3 and 4 include all the controls. Standard errors cluster at the state level. One, two, and three stars denote 10, 5, and 1 percent significance levels respectively.

The results are reported in Table 7. Mimicking the results of Panel C in Table 6, we show that, unconditionally, Mexicans seem to consume around 27 percent less than other households. This may be because they earn less or because they have different characteristics than natives that explain consumption patterns. When controlling for both in Column 4, we see that Mexican households consume around 10

[27]For this section we use the variable "totexpcq" from the Consumer Expenditure Survey. This variable combines expenditures on all items.

Figure 8: Return migration



Notes: This figure shows estimates of survival rates and return migration rates by age group. The graph on the left compares the size of natives and immigrants (who arrived before 2000) in Census years 2000 and ACS 2010 to estimate survival rates by age group. The graph on the right subtracts native survival rates from immigrant survival rates to obtain estimates of return migration rates by age group.

percent less than other households. This is consistent with the remittances sent to their home countries, or with them saving more for future consumption. We investigate whether future consumption in the home country is a potentially important channel in the following section.

3.2.4 Return migration

A final and very important reason why immigrants care about price indices in their home country is that many of them likely plan to return home at some point during their lifetime (Dustmann and Gorlach, 2016; Lessem, Forthcoming; Dustmann and Weiss, 2007; Dustmann, 2003, 1997).

To the best of our knowledge, there are no large, representative data sets directly documenting return migration patterns. This would require observations both in the destination country and in the home country over a certain period of time. While there are some data sets that make this possible, they are generally not very comprehensive.

To obtain a better sense of general return migration patterns in the United States, we turn to Census data. In particular, we can track the size of cohorts of immigrants and natives across Censuses and use information on immigrants' year of arrival to see how many of them are "missing" in the following Census–and thus likely to have returned to their home countries.

The left-hand graph in Figure 8 plots these survival rates by age cohort. For example, we observe that more than 98 percent of the natives aged between 25 and 30 in 2000 are still present in the 2010 ACS. This survival rate declines with age. For example, for the population that in 2000 was between 45 and 50 years old, the survival rate decreases to around 94 percent. When we carry out the same exercise for immigrants that arrived in the US before 2000, the survival rates decline substantially.[28]

In the graph on the right-hand side, we estimate return migration rates by taking the difference in

[28]We use the years 2000 and 2010 because there are strong reasons to suspect that there is some undercount of immigrants in Censuses prior to 2000. For example, the number of Mexican immigrants that claim to have arrived before 1990 in the Census 2000 is larger than the total number of Mexicans observed in the 1990 Census. See also Hanson (2006).

survival rates between immigrants and natives. This is a good estimate if mortality rates for the same age cohort are similar in both immigrants and natives. In this graph in Figure 8, we observe that return migration is likely to be very high for younger cohorts and converges to 0 for older cohorts. That is, more than 10 percent of the immigrant population aged between 25 and 30 in 2000 are no longer in the United States by 2010. We begin the series at age 25, since these immigrants are already likely to be working in the US. Return migration rates are even higher for younger cohorts.

This means that for a large number of immigrants, future consumption takes place in a country other than the United States–possibly their home country. Thus, given that immigrants are likely to return and to care about future consumption, return migration patterns give additional support to the idea that immigrants partly take into account the price index in their country of origin when choosing their optimal location in the US.

4 Model

In this section, we introduce a quantitative model that can account for all the facts shown above and estimate it using US Census data for the years 1990, 2000, and 2010.

The two key aspects of the model are the differences in preferences between natives and immigrants and the modeling of the labor market. The only difference between natives and immigrants is that immigrants can consume in their countries of origin while natives consume only locally. We allow for some degree of substitution between consuming locally and in the country of origin, which is parametrized by a constant elasticity of substitution (CES) function. Second, labor markets are not perfectly competitive. Under perfect competition, differences in the wages of workers who are perfect substitutes in the production function would be competed away. This has been widely recognized in the discrimination literature since Becker (1957). Wage differences for similar workers can, instead, be sustained in equilibrium when there are frictions in the labor market (Black, 1995). We need this to be true in order to obtain the result that part of the value of living in a given location for the different groups of workers is reflected in wages.

It is worth emphasizing that while we take a stance on some functional forms to parametrize preferences and the labor market, the model could be made much more general. In essence, the conditions required to generate results that are in line with the evidence presented above are simply that a) immigrants have an extra normal good that they value and b) that part of the value of living in a location be observed in wages.[29]

Finally, it is also worth emphasizing that we have opted for the simplest quantitative version of the model that delivers results that are in-line with the data. Many other things that the literature has emphasized, like the role of migrant networks (see for example Munshi (2003) and Jaeger (2007)), can easily be incorporated into the model. We prefer not to incorporate them given the orthogonal role that they seem to play in the data, see Appendix B.1 and the discussions in Section 3.

[29]More concretely, the utility of consuming very small quantities in the home country should go to minus infinity.

4.1 Location choices

The utility function in location c for an individual i from country of origin j is given by:

$$\ln U_{ijc} = \rho + \ln A_c + \alpha_t \ln C^T_{jc} + (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\frac{\alpha_l}{\alpha_l+\alpha_f}(C^{NT}_{jc})^{\frac{\sigma-1}{\sigma}} + \frac{\alpha_f}{\alpha_l+\alpha_f}(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}}\right) + \varepsilon_{ijc}$$

where α_t denotes the share of consumption devoted to tradable goods, and where α_l and α_f denote the weight of consumption in local non-tradable and foreign non-tradable goods, respectively. Tradable goods are denoted by C^T and the basket of non-tradable goods is denoted by C^{NT}. Within non-tradable goods, σ is the elasticity of substitution between local and foreign non-tradables. Note that there are alternative interpretations for what C^{NT}_j really means. It could mean consumption in non-tradables in the home country, remittances sent to relatives, or future consumption in the home country. We do not explicitly model these different potential channels. We prefer to use a simpler formulation that encapsulates all of them, rather than attempting to model the specificities that each of these channels may exhibit.[30] C^{NT}_{jc} should be thought, in the context of the model, as consumption of housing and other non-tradable goods available in location c.

Importantly, the various α_i govern the share of expenditure on the various types of goods. The difference between natives and immigrants is that for natives α_f is assumed to be zero, as stated more formally below. Besides this, ρ is a constant that ensures that there is no constant in the indirect utility function to be derived in what follows. ε is an extreme-value distributed idiosyncratic taste parameter for living in location c. A_c denotes local amenities.

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

$$p^T C^T_{jc} + p_c C^{NT}_{jc} + p_j C^{NT}_j \leq w_{jc}.$$

We define $\alpha_t + \alpha_l + \alpha_f = 1$ and the auxiliary parameters $\bar{\alpha}_l = \frac{\alpha_l}{\alpha_l+\alpha_f}$ and $\bar{\alpha}_f = \frac{\alpha_f}{\alpha_l+\alpha_f}$. By utility maximization, we then obtain the following indirect utility of living in each location (derivation in Appendix A.1):

$$\ln V_{ijc} = \ln V_{jc} + \varepsilon_{ijc} = \ln A_c + \ln w_{jc} - (1-\alpha_t)\ln \bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) + \varepsilon_{ijc},$$

where

$$\bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) = (\bar{\alpha}_l^\sigma p_c^{1-\sigma} + \bar{\alpha}_f^\sigma p_j^{1-\sigma})^{\frac{1}{1-\sigma}}.$$

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 parameter. Given the distribution of ε, the outcome of this maximization gives:

[30] Moreover, it is very plausible that the importance of each of these channels differs from one type of immigrant to another. For instance, remittances may be more relevant for less skilled immigrants, while future consumption may be more relevant for more skilled immigrants. We do not attempt to address this heterogeneity in this paper.

$$\pi_{jc} = \frac{V_{jc}^{1/\lambda}}{\sum_k V_{jk}^{1/\lambda}} = \left(\frac{V_{jc}}{V_j}\right)^{1/\lambda}, \tag{4.1}$$

where λ is the parameter governing the variance of ε_{ijc} and $V_j = (\sum_k V_{jk}^{1/\lambda})^{\lambda}$. π_{jc} is the share of workers from country j that decide to live in city c as a function of indirect utilities. Note that indirect utility increases in wages and local amenities and decreases in local prices. Thus, locations with higher wages, higher amenity levels, and lower price indices will attract more people.

4.2 Firms' technology

Firms' technology is given by the following linear production function for tradables:

$$Q_c^T = B_c L_c \tag{4.2}$$

where $L_c = \sum_i L_{icj}$ is the sum of all the workers that live in c and come from origin j. B_c is the technological level of the city c. If it depends on L_c, we have agglomeration externalities. In particular, we can assume that $B_c(L_c) = B_c L_c^a$ with $a \geq 0$. We will come back to this point in Section 5, but we ignore it in the presentation of the model to keep it simple.[31]

The marginal revenue of hiring an extra worker is given by B_c. The cost of hiring an additional worker, possibly from origin j, is the wage that they receive, which we denote by w_{jc}. Thus, the extra profit generated by hiring an additional worker is given by $B_c - w_{jc}$. The average cost of hiring workers across all the cities is given by $\bar{w}$. Note that we can choose to use this as the numeraire. Using this, we obtain that wages are relatively close to 1. Thus, using a Taylor expansion, we have that $(B_c - w_{jc}) \approx B_c - 1 - \ln w_{jc} = \ln \tilde{B}_c - \ln w_{jc} = S_{jc}^F$. This expression is the value of a new hire.

4.3 Labor market

Labor markets are not competitive. Firms and workers meet and negotiate over the wage and split the total surplus of the match. A worker's surplus in matching with a firm is given by:

$$S_{jc}^W = \ln V_{jc}$$

Hence, we make the simplifying assumption that once located in a city, the worker's surplus no longer depends on the initial taste shock drawn and that his outside option to working is receiving an indirect utility of zero.[32] That is, a worker choosing city c will benefit from the local indirect utility.

The outcome of the negotiation between workers and firms is determined by Nash bargaining. Workers' weight in the negotiation is given by β. Thus, a share β of the total surplus generated by a match accrues to workers. Using this assumption, we can determine the wage levels of the various workers from country of origin j living in location c:

[31] For the model to have a solution, we need to make sure that $a < min\{\eta_c\}$, where η_c is the elasticity of housing supply that we introduce in Section 4.4.

[32] The basic results of this paper are not sensitive to the exact specification of the worker surplus as long as it depends positively on local wages and amenities and negatively on local price levels.

$$\ln w_{jc} = -(1-\beta)\ln A_c + \beta \ln \tilde{B}_c + (1-\beta)(1-\alpha_t)\ln \bar{p}_{jc} \tag{4.3}$$

This equation shows standard results from the spatial economics literature. Higher wages in a city reflect either lower amenity levels, high local productivity, or high local price indices.

4.4 Housing market

There are congestion forces because housing supply is inelastic. This gives the standard relationship between local prices and city size:

$$\ln p_c = \eta_c \ln L_c$$

This determines local price indices of non-tradable goods in the model. Note that we allow η_c to vary by city.

4.5 Properties

Given these primitives of the model, in this subsection we derive a number of properties. These properties are the basis for the structural estimation described in Section 5.

The difference between natives and immigrants is the weight they give to local and foreign price indices:

Assumption. *Natives only care about local price indices so that* $\alpha_f = 0$ *and* $\alpha_l = \alpha$. *Immigrants care about local and foreign price indices so that* $\alpha_f \neq 0$ *and* $\alpha_l + \alpha_f = \alpha$.

Proposition 1. *Under the above assumption and the assumptions made on the modeling choices, there is a positive gap in wages between natives and immigrants. This gap increases in the local price index and the effect of the local price index is larger when* p_j *is low. The wage gap is given by the following expression:*

$$\ln w_{Nc} - \ln w_{jc} = (1-\beta)(1-\alpha_t)\ln p_c - (1-\beta)(1-\alpha_t)\ln \bar{p}_{jc} \tag{4.4}$$

Proof. Appendix A.2

□

It is worth noting that in the model, differences in the price index of origin do not play a direct role in the special case of $\sigma = 1$ as then we have a Cobb-Douglas utility function that combines the consumption of local and foreign non-tradable goods. The result of this maximization problem is that the demand for each good is a constant portion of total income. If instead we assume that there is a high degree of substitutability between local and home consumption, we obtain the result that the immigrants' share of consumption in countries of origin with higher price indices is lower, hence the difference in the importance of local price indices for immigrants and natives decreases.

In Section 3, we also showed empirically that immigrants concentrate in higher proportions in larger, more expensive cities. This can be summarized in the following proposition:

Proposition 2. *Under assumption above, and the assumptions made on the modeling choices, immigrants concentrate in expensive cities. The spatial distribution of immigrants relative to natives is given by:*

$$\ln \frac{\pi_{jc}}{\pi_{Nc}} = \frac{1}{\lambda} \left(\beta(1-\alpha_t)\ln p_c - \beta(1-\alpha_t)\ln \bar{p}_{jc}\right) + \ln \frac{\sum_k \left(A_k \tilde{B}_k / L_k^{\eta_k(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}{\sum_k \left(A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}} \tag{4.5}$$

Proof. Appendix A.2 □

These two propositions are linked directly to the facts that we report in Section 3. They show the concentration of immigrants and the fact that immigrants receive lower wages than natives in expensive cities. If the relationship between local prices and population is positive (which is given by the inelastic supply of housing), these two propositions also show the relationship between city sizes and immigrants' location choices and wages. We can use the allocation of workers across locations to obtain the equilibrium size of the city. In particular, the following proposition characterizes the distribution of workers across cities given the total native and immigrant populations (L_N and L_j for each country of origin j).

Proposition 3. *The equilibrium size of the city increases in local productivity and amenities according to:*

$$L_c = (A_c \tilde{B}_c)^{\frac{\beta}{\lambda}} \sum_j \frac{L_j / \bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} + \frac{(A_c \tilde{B}_c / L_c^{\eta_c(1-\alpha_t)})^{\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / L_k^{\eta_k(1-\alpha_t)})^{\frac{\beta}{\lambda}}} L_N \tag{4.6}$$

Proof. Appendix A.2 □

Note that this proposition also means that immigrants make large cities even larger. That is, because they care less than natives about the cost of large cities (i.e., congestion), they enable big cities to become larger. Moreover, it shows that cities are large because they are either productive (B_c) or pleasant to live in (A_c). Thus, conditional on amenity levels, immigration concentrates the population in more productive cities.

To see the aggregate effect of immigration on total output via their location choices, we can obtain an expression of total output per capita depending on the immigrant shares.

Proposition 4. *All else equal, the aggregate output per capita increases with the share of immigrants in the economy. Aggregate output per capita is given by the expression:*

$$q = \sum_c \left[(A_c \tilde{B}_c^{\frac{\beta+\lambda}{\beta}})^{\frac{\beta}{\lambda}} \sum_j \frac{\frac{L_j}{L} / \bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} \right] + \frac{\sum_c (A_c \tilde{B}_c^{\frac{\beta+\lambda}{\beta}} / L_c^{\eta_c(1-\alpha_t)})^{\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / L_k^{\eta_c(1-\alpha_t)})^{\frac{\beta}{\lambda}}} \frac{L_N}{L} \tag{4.7}$$

Proof. Appendix A.2 □

What this proposition really means is that, holding total population constant, if there are more immigrants, total output is higher.

5 Estimation of the model and output and welfare analysis

In this section, we estimate the model presented in Section 4. For each country of origin, there are two key equations that the model generates, from which we can obtain the three key structural parameters (which we assume to be common across immigrants of different countries of origin).[33] The first key parameter is the weight of home-country goods in consumption ($\bar{\alpha}_f$), the second is the elasticity of substitution between home-country goods and local goods (σ), and the third is the sensitivity of migrant location choices to local conditions (λ).[34] We calibrate the rest of parameters using previous literature.

5.1 Model estimation

To obtain the first two key parameters, we use the relationship between wage gaps and city prices across countries of origin. We estimate the model combining 1990, 2000 and 2010 Census and ACS data and World Bank price-level data. For this estimation we use the exact same data that we used for documenting immigrant heterogeneity in Section 3.1.4, see column (2) of Table 2.[35]

First, we use the relationship between wage gaps and local price indices that the model generates at the country of origin-metropolitan area level given by Equation 4.4 to estimate $\{\bar{\alpha}_f, \sigma\}$. More specifically, from this equation we obtain that:

$$\frac{\partial \ln \frac{w_{N,c}}{w_{j,c}}}{\partial \ln p_c} = (1-\beta)(1-\alpha_t)(1+\Omega_l)$$

And

$$\frac{\partial \ln \frac{w_{N,c}}{w_{j,c}}}{\partial \ln p_c \partial \ln p_j} = (1-\beta)(1-\alpha_t)\Omega_l(1-\Omega_l)$$

where $\Omega_l = \frac{\bar{\alpha}_l^\sigma p_c^{1-\sigma}}{\bar{\alpha}_l^\sigma p_c^{1-\sigma} + \bar{\alpha}_f^\sigma p_j^{1-\sigma}}$ is the share of consumption on local goods and is a function that depends on the two parameters of interest $\bar{\alpha}_f$ and σ and on the relative price index of foreign to local goods. We evaluate this equation at the average city and country of origin. In particular, we use the fact that on average home country price indices are 84 percent of the price index in the average US city.

From column (2) of Table 2 we obtain that:[36]

$$(1-\beta)(1-\alpha_t)(1+\Omega_l) = 0.487$$

$$(1-\beta)(1-\alpha_t)\Omega_l(1-\Omega_l) = 0.0491$$

[33]We could obviously allow for some heterogeneity across countries of origin that is not related to economic incentives but rather to some idiosyncratic preferences. This would likely explain the data better, but would obscure the explanatory power of our model.

[34]An alternative strategy would have been to use the suggestive evidence of how much the home country matters for immigrants shown in Section 3.2 and estimate the model using this information in conjunction with the labor-market data. We prefer the alternative of estimating the model using exclusively labor-market data as we believe that it better highlights the economic importance of the mechanism that we study in this paper.

[35]Using column (4) in that Table would result in similar estimates. We use column (2) because we use the model to explain cross-sectional moments.

[36]In Table 2 we only report the interaction between local prices and prices at origin, since that is the focus of that table. The coefficient in the column on the the local price index is the one indicated here. This is comparable to the coefficient reported in Figure 5.

This is a (non-linear) system of two equations and four unknowns: $\{\bar{\alpha}_f, \sigma, \beta, \alpha_t\}$. We can reduce the dimensionality of the parameter space by assuming that $\beta = .3$ and $1 - \alpha_t = .65$. This means that we assume that the weight of workers when bargaining for wages is 30 percent, and that the share of consumption that goes to non-tradables is 65 percent. There are a number of estimates in the literature on the workers' bargaining weight. Recent work, however, suggests that an estimate of 30 percent is reasonable. For example, Lise et al. (2016) obtain an estimate of 30 percent for college graduates, and of around 20 percent for high school graduates or less. In our context, low estimates help us explain the data better, so using a workers' bargaining weight of 30 percent is a conservative strategy within our framework. Note that, an estimate of 30 percent means that firms can extract quite some value from worker's location decisions.[37] This means, in the context of our model, that wages reflect to a large extend the value of living in each location. Estimates of the weight of tradable goods in overall consumption are somewhat elusive in the literature. An estimate of 35 percent of consumption spent on tradables is in-line with the relative size of tradable and non-tradable sectors estimated in Mian et al. (2013).

Once we have assumed specific values for α_t and β we are left with a system of two equations and two unknowns. We solve this system (numerically) and obtain the values for $\bar{\alpha}_f = 0.16$ and $\sigma = 1.29$. This parameter estimates have clear economic meaning. The fact that $\bar{\alpha}_f$ is around 16 percent means that the distribution of immigrants across locations and their wages is consistent with the fact that, on average, immigrants consume around 16 percent of non-tradables in their country of origin. This represents around 10 percent of their total consumption (α_f in the utility function defined above), since 65 percent of income is spent, on average, on non-tradables. This number coincides with the number estimated in Table 7 using consumption data directly. The elasticity of substitution σ is identified from the heterogeneity across countries of origin. An elasticity larger than one means that immigrants substitute consuming locally for home country consumption. Thus, immigrants from poorer, lower price index countries consume relatively more in their country of origin than immigrants from richer origins.

To obtain λ we only need to use equation 4.5 using the estimates of β, α_t, σ, and α_f. From these we can obtain the relevant price index for each country of origin, and estimate equation 4.5 with linear least squares. We obtain that $\frac{1}{\lambda}\beta(1-\alpha_t) = 4.04$ with a standard error of 0.07. From this we can back up $\lambda = 0.048 \approx 0.05$.[38]

For the productivity and amenity levels across cities, and the force of local agglomeration forces we rely on prior literature. For the productivity and amenity levels, we use Albouy (2016). In a model similar to ours, but where the role of immigrants is not taken into account, Albouy (2016) estimates productivities and amenity levels for 168 (consolidated) metropolitan areas in our sample; we too use these below.[39] For the housing-supply elasticities, we rely on Saiz (2010).[40] Finally, we use an estimate of local agglomeration forces that is consistent with the consensus in the literature (see Combes and

[37] See also the survey article Manning (2011). In recent papers, the range of estimates moves from 5 percent to 34 percent.

[38] We use 2 digit approximations. Nothing changes if we use higher precision.

[39] An alternative would be to allow these underlying amenities to depend on migration networks. This may change the estimation of the model, and would probably make the model closer to the data as suggested by the evidence presented in Section B.1. We abstract from this in the paper to highlight our mechanism.

[40] Saiz (2010) reports housing-supply elasticities at the primary metropolitan statistical area (PMSA), so we use Albouy (2016)'s crosswalk between PMSAs and consolidated metropolitan statistical areas (CMSAs).

Gobillon (2014) and Duranton and Puga (2004)).

Once we fix this set of parameters, we use the model to perform counterfactuals. Table 8 shows the main estimates.

Table 8: Model estimates

Variable	Estimate	Source
Share of consumption on tradable goods (α_t)	0.35	Mian et al. (2013)
Workers' bargaining weight (β)	0.3	Lise et al. (2016)
Share of home goods consumption (α_f)	0.10	Estimated
Sensitivity to local conditions (λ)	0.05	Estimated
Elasticity of substitution home-local goods (σ)	1.29	Estimated
Amenity levels (A_c)		Albouy (2016)
Productivity levels (B_c)		Albouy (2016)
House-price supply elasticity (η_c)		Saiz (2010)
Local agglomeration (a)	0.05	Combes and Gobillon (2014)

Notes: This table shows the estimates of the structural parameters of the model.

5.2 Immigration and economic activity

5.2.1 Comparison model vs. data

Once we have all the parameters–those that we estimate ourselves and those that we borrow from the literature–we can compare the quantitative predictions of our model with the data. Using various moments of the data should serve to show that our model can quantitatively match some of the key features of metropolitan-level cross-sectional US data. We demonstrate this below.

At an aggregate level, the model estimated exclusively on labor market data delivers an estimate of the weight of the home country on overall consumption that is very similar to the direct estimates that we obtained using consumption expenditure survey data. In section 3.2.3 we showed that Mexican immigrants consume on average, 11.5 percent less on local goods than similarly looking natives. We can directly compare this estimate with the estimate $\alpha_f = \bar{\alpha}_f * (1 - \alpha_t) = 0.16 * 0.65 = 10.4\%$.

At a disaggregate, metropolitan-area, level, we can compare the predictions of the model against data. In Figure 9, we plot a number of variables against the underlying productivity levels in each city taken from Albouy (2016). Note that our estimation of the model is at the city-country of origin level, while the moments in Figure 9 are at the metropolitan area level. The underlying productivity is the primitive parameter that drives our results on both location and wage gaps. In general, we do a better job of explaining the wage data than the population data.

The top-left graph in Figure 9 shows that population distribution across US cities in the model is slightly less concentrated in large cities than in the data. In both cases, there is a positive relationship, but the positive relationship between city size and productivity is weaker in the model. Another difference between the model and the data is that there is more dispersion in the data than in the model. This is not surprising since the only source of dispersion in the model is the differences in amenities between locations of similar productivity, while in the data the sources of heterogeneity may come from other channels. Meanwhile, the model does a good job of obtaining the relationship between wages and productivity.

Figure 9: Model and data, metropolitan area-level moments

Notes: This figure compares the data and the model. Each dot represents a city. We use the 168 consolidated metropolitan areas used in Albouy (2016). See the text for the details on the various parameters of the model. In this figure, we assume that the endogenous agglomeration forces are 5 percent (i.e., $a = 0.05$).

This is shown in the top-right graph in Figure 9. Again, the relationship is similar even though there is more dispersion in the data than in the model.

The model also explains slightly better native-immigrant wage gaps (aggregated at the city level), than immigrant shares. That is, the model, which is estimated at the country of origin-metropolitan area level, delivers a positive relationship between immigrant shares and productivity at the city level that mimics the relationship in the data. As before, though, the model delivers a somewhat weaker relationship than the data. It is interesting to see that there are some important outliers in terms of immigrant shares. These smaller metropolitan areas with a high share of immigrants are always close to the Mexican border. This is something that the model cannot match as we have already discussed in Section 2. Similarly, the model is capable of generating a negative relationship between native-immigrant wage gaps at the city level that is similar to the one observed in the data, and that is at the root of the main findings of this paper.

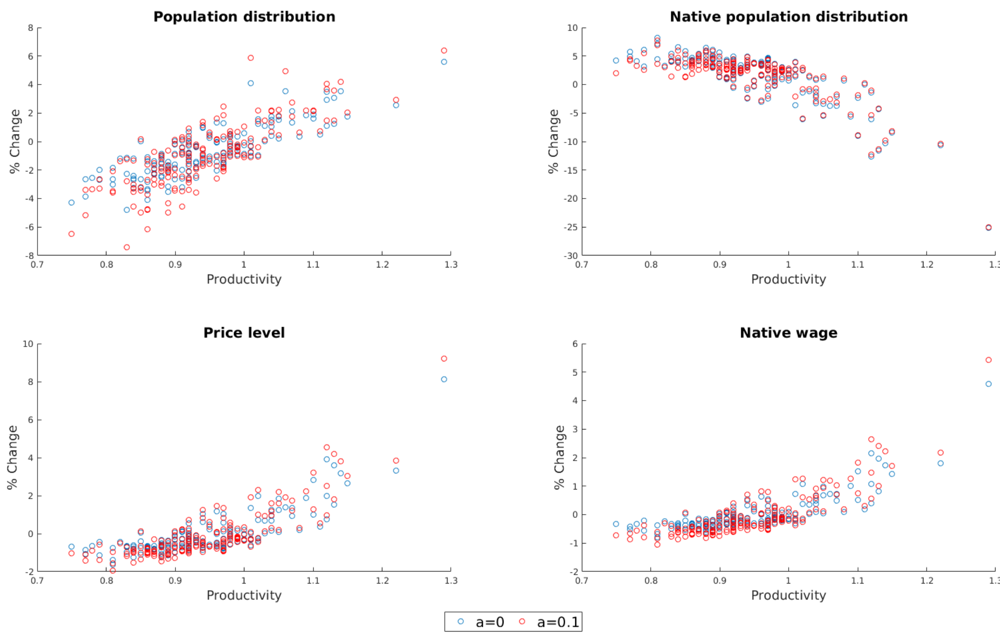
Overall, it seems that our estimated model is quantitatively similar to the data, and can thus be used to perform some counterfactual experiments that should help to shed light on the importance of immigrants in a number of outcomes.

5.2.2 The distribution of economic activity and general equilibrium

The main counterfactual exercise that we undertake is to examine what happens if, keeping total population constant, we increase the share of immigrants (holding constant the distribution of countries of origin). This uses Equation 4.5, previously introduced. That is, in this equation, we first compute the distribution of population across metropolitan areas assuming that there are no immigrants, and we then carry out the same exercise with current immigration levels of around 15 percent. We perform this exercise both with and without agglomeration forces (i.e., with $a = 0$ and $a > 0$ in equation 4.2).

In Figure 10, we plot the change in a number of outcome variables between the predictions of the model with and without immigrants. Effectively, this measures the role of migration on the economy through their residential choices.

Figure 10: Effect of immigrants



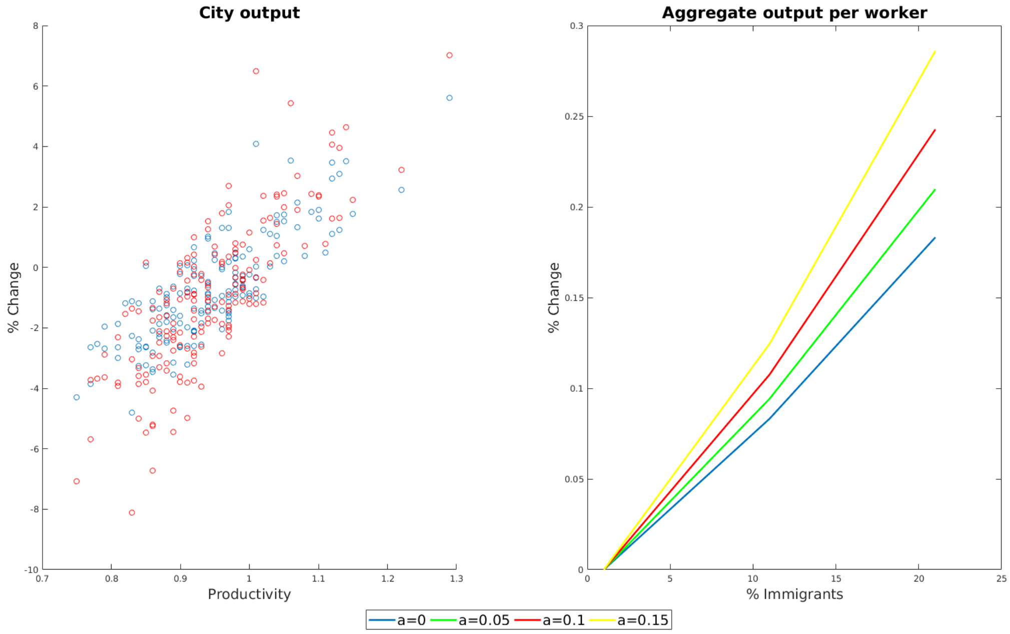
Notes: This figure compares the model with and without agglomeration forces. Each dot represents a city. We use the 168 consolidated metropolitan areas used in Albouy (2016). See the text for details of the various parameters of the model.

It is apparent from Figure 10 that migration makes more productive cities larger. This is the basis of the output gains that come from the differential location choices of immigrants relative to natives. The graph shows how the most productive metropolitan areas in the United States are as much as between 4 and 8 percent larger as a result of current immigration levels than they would have been if immigrants had decided on residential locations in the way natives do. These gains are slightly larger in the presence of positive agglomeration forces.

As a result of migrants' strong preference for more productive cities and the pressure that this decision puts on local price indices, which can be seen in the bottom-left graph in Figure 10, natives are displaced from more productive cities into less productive ones, as can be seen in the top-right graph in Figure 10. In fact, current levels of migration can potentially account for a significant part of the increase in local price indices in more productive cities.

The bottom-right graph in Figure 10 shows what happens to natives' wages, which move in the same direction as the city price levels. With agglomeration forces, both positive and negative changes are more pronounced than the price-level changes because we see additional effects of population on wages

Figure 11: Effect of immigrants on the distribution of output and on total output



Notes: This figure compares the model with and without agglomeration forces. Each dot in the graph on the left represents a city. We use the 168 consolidated metropolitan areas used in Albouy (2016). See the text for details of the various parameters of the model. The graph on the right shows the relationship between total output and aggregate immigrant share predicted by the model.

through productivity. It is remarkable to note that immigrant location choices also help to explain the divergence in nominal incomes between metropolitan areas, in line with the evidence reported in Moretti (2013). In the context of the model, however, real-wage inequality between small and large locations does not increase as a result of immigration, as we explain in the following section.

In Figure 11, we investigate the effect of immigration on output. Two things stand out. First, immigration moves economic activity from low-productivity locations to high-productivity ones. These gains are even greater in the presence of agglomeration forces. These output gains in more productive cities are in the order of 4 to 8 percent. Second, immigration induces overall output gains. The gain in size of the most productive cities translates into output gains for the entire country, even if low-productivity places lose out.

The magnitude of these overall gains depends crucially on agglomeration forces. We show this in the right-hand graph in Figure 11. Immigration shares, at around 20 percent, translate into total output gains per capita in the range of 0.2 to 0.3 percent. It is also interesting to note that the increase in aggregate output resulting from immigrant location choices is convex in the share of migrants. Thus, immigration results in overall gains and, perhaps more prominently, important distributional consequences, particularly between more and less productive locations.

5.2.3 Discussion of welfare consequences

While it is easy to talk about wages, local price indices, and the distribution of economic activity and populations across locations using the model, it is slightly more difficult to use the model to obtain clear results on the effect that migration has on welfare. These difficulties stem from the fact that there are essentially three different types of agent in the model and the consequences of immigration are heterogeneous among them.

The first type of agent in the model, which has been the focus for most of the paper, is workers. While native workers in larger, more productive cities benefit from immigration in terms of wages, they lose out in terms of welfare. This is a consequence of the fact that we are using a spatial equilibrium model and we need to have congestion forces dominate agglomeration forces. Higher levels of immigration result in higher nominal wages in more productive cities than in less productive ones, but the increase in local price indices is larger than the change in nominal wages. This ensures that a unique spatial equilibrium exists with both high and low levels of immigration, but it also implies that native workers in more productive cities lose out relative to native workers in less productive cities with higher levels of immigration.

However, this is not the case for firm owners and landowners. While we have not modeled these explicitly, it is quite clear that firms and landowners in more productive cities benefit more than those in less productive cities. This is because firms in the model do not pay land rents (something we could include) and because immigrants put pressure on housing costs.

Thus, whether immigration increases welfare in high- relative to low-productivity areas depends crucially on our assumptions about who owns the land and who owns the firms. Given that these are simply assumptions, we prefer not to make overall welfare calculations.[41]

6 Conclusion

This paper begins by documenting that immigrants concentrate in larger, more expensive cities and that their earnings relative to natives are lower there. These are very strong patterns in the US data. We obtain these results using a number of specifications, time periods, and data sets. They are also robust to controlling for immigration networks and only attenuate for immigrants whose countries of origin display similar levels of development as the United States or who have spent more time in the United States.

Taking all this evidence together, we posit that these patterns emerge because a share of immigrants' consumption is affected not by local price indices but rather by prices in their country of origin. That is, given that immigrants send remittances home and are more likely to spend time and consume in their countries of origin, they have a greater incentive to live in high-nominal-income locations than natives.

We build a quantitative spatial equilibrium model with frictions in the labor market to quantify the importance of this mechanism. We estimate the model and show that the differential location choices of immigrants relative to natives have two consequences. First, they move economic activity from low-

[41] One possibility is to assign output to workers and firms according to aggregate, nation-wide, labor and capital shares. See Hsieh and Moretti (2017).

productivity places to high-productivity places. Second, this shift in the patterns of production induces overall output gains. Relying on country of origin heterogeneity, we estimate these gains to be in the order of 0.3 percent of output per capita with current levels of immigration.

This paper extends some of the insights in the seminal contribution of Borjas (2001). Borjas' main argument is that immigrants choose the locations where demand for labor is higher, thus helping to dissipate arbitrage opportunities across local labor markets. We show in this paper that immigrants systematically choose not just locations with higher demand for labor but specifically more productive locations, and we quantify how much these choices contribute to overall production in the United States.

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A Proofs

A.1 Derivation of indirect utility

Consider the following utility in location c for an individual i from country of origin j:

$$U_{ijc} = \rho + \ln A_c + \alpha_t \ln C_{jc}^T + (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\frac{\alpha_l}{\alpha_l+\alpha_f}(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \frac{\alpha_f}{\alpha_l+\alpha_f}(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right) + \varepsilon_{ijc}$$
$$\text{s.t. } C_{jc}^T + p_c C_{jc}^{NT} + p_j C_j^{NT} \leq w_{jc}$$

Let

$$\begin{aligned}
\bar{\alpha}_l =& \frac{\alpha_l}{\alpha_l+\alpha_f} \\
\bar{\alpha}_f =& \frac{\alpha_f}{\alpha_l+\alpha_f}
\end{aligned}$$

We also take note of the following relationships:

$$\bar{\alpha}_l + \bar{\alpha}_f = 1$$
$$\alpha_t + \alpha_l + \alpha_f = 1$$

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

$$U_{ijc} = \rho + \ln A_c + \alpha_t \ln C_{jc}^T + (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right) + \varepsilon_{ijc}$$
$$\text{s.t. } C_{jc}^T + p_c C_{jc}^{NT} + p_j C_j^{NT} \leq w_{jc}$$

Note that

$$\begin{aligned}
&\lim_{\sigma\to 1}(1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right) = \begin{bmatrix}0\\ \hline 0\end{bmatrix} \\
=&(1-\alpha_t)\lim_{\sigma\to 1}\frac{\frac{\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}}\ln C_{jc}^{NT}\frac{1}{\sigma^2} + \bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\ln C_j^{NT}\frac{1}{\sigma^2}}{\bar{\alpha}_l(C_j^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}}}{\frac{1}{\sigma^2}} \text{ by l'Hopital} \\
=&(1-\alpha_t)\lim_{\sigma\to 1}\frac{\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}}\ln C_{jc}^{NT} + \bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\ln C_j^{NT}}{\bar{\alpha}_l(C_j^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}} \\
=&(1-\alpha_t)\left(\bar{\alpha}_l\ln C_{jc}^{NT} + \bar{\alpha}_f\ln C_j^{NT}\right) \\
=&\alpha_l\ln C_{jc}^{NT} + \alpha_f\ln C_j^{NT}
\end{aligned}$$

Thus,

$$\lim_{\sigma\to 1} U_{ijc} = \rho + \ln A_c + \alpha_t \ln C_{jc}^{T} + \alpha_l \ln C_{jc}^{NT} + \alpha_f \ln C_j^{NT} + \varepsilon_{ijc}$$

which is the utility function using the Cobb-Douglas aggregation, possibly with a different ρ. We solve the problem in two stages:

- **Stage 1**: Define an auxiliary variable E and find the optimal decisions $C_{jc}^{NT*}(p_c, p_j, E)$ and $C_j^{NT*}(p_c, p_j, E)$ to the following maximization problem

$$\begin{aligned}&\max \ \ (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l (C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right)\\ &\text{s.t. } \ p_c C_{jc}^{NT} + p_j C_j^{NT} = E\end{aligned}$$

  Let

$$\tilde{V}(p_c, p_j, E) = (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l (C_{jc}^{NT*})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT*})^{\frac{\sigma-1}{\sigma}}\right)$$

- **Stage 2**: Solve for $C_j^{T*}(p_c, p_j, w_{jc})$ and $E^*(p_c, p_j, w_{jc})$ of the maximization problem

$$\begin{aligned}&\max \ \rho + \ln A_c + \alpha_t \ln C_{jc}^{T} + \tilde{V}(p_c, p_j, E)\\ &\text{s.t. } \ C_{jc}^{T} + E \le w_{jc}\end{aligned}$$

Stage 1

$$\begin{aligned}&\max \ \ (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l (C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right)\\ &\text{s.t. } \ p_c C_{jc}^{NT} + p_j C_j^{NT} = E\end{aligned}$$

The associated Lagrangian is

$$\mathcal{L} = (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l (C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right) + \lambda(E - p_c C_{jc}^{NT} - p_j C_j^{NT})$$

First-order conditions are given by

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial C_{jc}^{NT}} &: \ \frac{(1-\alpha_t)\bar{\alpha}_l (C_{jc}^{NT})^{\frac{-1}{\sigma}}}{\bar{\alpha}_l (C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT})^{\frac{\sigma-1}{\sigma}}} - p_c\lambda = 0\\ \frac{\partial \mathcal{L}}{\partial C_{j}^{NT}} &: \ \frac{(1-\alpha_t)\bar{\alpha}_f (C_{j}^{NT})^{\frac{-1}{\sigma}}}{\bar{\alpha}_l (C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT})^{\frac{\sigma-1}{\sigma}}} - p_j\lambda = 0\end{aligned}$$

Dividing the two first-order conditions, we obtain the following relationship

$$\frac{\bar{\alpha}_l}{\bar{\alpha}_f}\left(\frac{C_{jc}^{NT}}{C_j^{NT}}\right)^{\frac{-1}{\sigma}} = \frac{p_c}{p_j} \Rightarrow C_{jc}^{NT} = \left(\frac{\bar{\alpha}_f p_c}{\bar{\alpha}_l p_j}\right)^{-\sigma} C_j^{NT}$$

Using this relationship and the budget constraint, we find

$$C_{jc}^{NT} = \frac{\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E$$

$$C_{j}^{NT} = \frac{\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E$$

Thus, the maximized objective function is

$$\begin{aligned}
\tilde{V} &= (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l\left(\frac{\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E\right)^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f\left(\frac{\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E\right)^{\frac{\sigma-1}{\sigma}}\right) \\
&= (1-\alpha_t)\ln E + (1-\alpha_t)\frac{1}{\sigma-1}\ln\left(p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}\right) \\
&= (1-\alpha_t)\ln E - (1-\alpha_t)\ln \bar{p}(\bar{\alpha}_l, \bar{\alpha}_f)
\end{aligned}$$

where $\bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) = (\bar{\alpha}_l^{\sigma} p_c^{1-\sigma} + \bar{\alpha}_f^{\sigma} p_j^{1-\sigma})^{\frac{1}{1-\sigma}}$

Stage 2

$$\begin{aligned}
&\max\ \rho + \ln A_c + \alpha_t \ln C_{jc}^T + (1-\alpha_t)\ln E + (1-\alpha_t)\frac{1}{\sigma-1}\ln \bar{p}(\bar{\alpha}_l, \bar{\alpha}_f) \\
&\text{s.t. } C_{jc}^T + E \le w_{jc}
\end{aligned}$$

The associated Lagrangian is

$$\mathcal{L} = \rho + \ln A_c + \alpha_t \ln C_{jc}^T + (1-\alpha_t)\ln E - (1-\alpha_t)\ln \bar{p}(\bar{\alpha}_l, \bar{\alpha}_f) + \lambda(w_{jc} - C_{jc}^T - E)$$

The first-order conditions are

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial C_{jc}^T} &: \frac{\alpha_t}{C_{jc}^T} - \lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial E} &: \frac{(1-\alpha_t)}{E} - \lambda = 0
\end{aligned}$$

Using these first-order conditions and budget constraints,

$$\begin{aligned}
C_{jc}^T &= \alpha_t w_{jc} \\
E &= (1-\alpha_t) w_{jc}
\end{aligned}$$

Thus, the optimal choices for consumption can be written as

$$
\begin{aligned}
C^T_{jc} &= \alpha_t w_{jc} \\
C^{NT}_{jc} &= \frac{\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}(1-\alpha_t)w_{jc} \\
C^{NT}_{j} &= \frac{\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}(1-\alpha_t)w_{jc}
\end{aligned}
$$

This solution can be shown to satisfy the first-order conditions of the original problem. If we let ρ be a constant such that the indirect utility function has no constant, the indirect utility function can be written as

$$
\boxed{\ln V_{ijc} = \ln V_{jc} + \varepsilon_{ijc} = \ln A_c + \ln w_{jc} - (1-\alpha_t)\ln \bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) + \varepsilon_{ijc}}
$$

where $\bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) = (\bar{\alpha}_l^{\sigma} p_c^{1-\sigma} + \bar{\alpha}_f^{\sigma} p_j^{1-\sigma})^{\frac{1}{1-\sigma}}$

A.2 Proofs of propositions

Assumption Natives only care about local price indices so that $\alpha_f = 0$ and $\alpha_l = \alpha$. Immigrants care about local and foreign price indices so that $\alpha_f \neq 0$ and $\alpha_l + \alpha_f = \alpha$.

Proof. **Proposition 1**

- $\ln w_{jc} = -(1-\beta)\ln A_c + \beta \ln \tilde{B}_c + (1-\beta)(1-\alpha_t)\ln p_{jc}$
- $\ln w_{Nc} = -(1-\beta)\ln A_c + \beta \ln \tilde{B}_c + (1-\beta)(1-\alpha_t)\ln p_c$

Thus,

$$
\ln w_{Nc} - \ln w_{jc} = (1-\beta)(1-\alpha_t)\ln p_c - (1-\beta)(1-\alpha_t)\ln p_{jc}
$$

Denote $W = \ln w_{Nc} - \ln w_{jc}$. We are interested in the sign of $\frac{\partial W}{\partial p_c}$.

$$
\begin{aligned}
W &= (1-\beta)(1-\alpha_t)\ln p_c - (1-\beta)(1-\alpha_t)\frac{1}{1-\sigma}\ln\left(\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}\right) \\
\frac{\partial W}{\partial p_c} &= \frac{(1-\beta)(1-\alpha_t)}{p_c} - \frac{(1-\beta)(1-\alpha_t)\bar{\alpha}_l^{\sigma} p_c^{-\sigma}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}} \\
&= (1-\beta)(1-\alpha_t)\frac{\frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}} > 0
\end{aligned}
$$

Also,

$$\begin{aligned}\frac{\partial^2 W}{\partial p_c \partial p_j} =&(1-\beta)(1-\alpha_t)\frac{\left(\frac{\bar{\alpha}_l^\sigma}{p_c^{\sigma-1}}+\frac{\bar{\alpha}_f^\sigma}{p_j^{\sigma-1}}\right)(1-\sigma)\frac{\bar{\alpha}_f^\sigma}{p_j^\sigma}-\frac{\bar{\alpha}_f^\sigma}{p_j^{\sigma-1}}(1-\sigma)\frac{\bar{\alpha}_f^\sigma}{p_j^\sigma}}{\frac{\bar{\alpha}_l^\sigma}{p_c^{\sigma-1}}+\frac{\bar{\alpha}_f^\sigma}{p_j^{\sigma-1}}}\\ =&(1-\beta)(1-\alpha_t)(1-\sigma)\frac{\bar{\alpha}_f^\sigma}{p_j^\sigma}\frac{\frac{\bar{\alpha}_l^\sigma}{p_c^{\sigma-1}}}{\frac{\bar{\alpha}_l^\sigma}{p_c^{\sigma-1}}+\frac{\bar{\alpha}_f^\sigma}{p_j^{\sigma-1}}}<0\end{aligned}$$

Thus, the gap in wages between natives and immigrants is increasing in the local price index. Furthermore, the effect of the local price index on the wage gap is larger for low p_j.

□

Proof. **Proposition 2**

Recall that

$$\pi_{jc}=\frac{V_{jc}^{1/\lambda}}{\sum_k V_{jk}^{1/\lambda}}=\left(\frac{V_{jc}}{V_j}\right)^{1/\lambda}$$

Thus,

$$\ln\pi_{jc}-\ln\pi_{Nc}=\frac{1}{\lambda}(\ln V_{jc}-\ln V_{Nc})-\frac{1}{\lambda}(\ln V_j-\ln V_N)$$

Using the definition of $\ln V_{jc}$ and the expression for the wage gap obtained above, we have

$$\begin{aligned}\ln V_{jc}-\ln V_{Nc} =&\ln w_{jc}-\ln w_{Nc}-(1-\alpha_t)\left(\ln\bar{p}_{jc}-\ln p_c\right)\\ =&-(1-\beta)(1-\alpha_t)\ln p_c+(1-\beta)(1-\alpha_t)\ln\bar{p}_{jc}-(1-\alpha_t)\left(\ln\bar{p}_{jc}-\ln p_c\right)\\ =&\beta(1-\alpha_t)\ln p_c+\beta(1-\alpha_t)\ln\bar{p}_{jc}\end{aligned}$$

Note that

$$\begin{aligned}\ln V_{jc} =&\ln A_c+\ln w_{jc}-(1-\alpha_t)\ln\bar{p}_{jc}\\ =&\ln A_c+\left(-(1-\beta)\ln A_c+\beta\ln\tilde{B}_c+(1-\beta)(1-\alpha_t)\ln\bar{p}_{jc}\right)-(1-\alpha_t)\ln\bar{p}_{jc}\\ =&\beta\ln A_c+\beta\ln\tilde{B}_c-\beta(1-\alpha_t)\ln\bar{p}_{jc}\end{aligned}$$

Thus,

$$V_{jc}=A_c^\beta\tilde{B}_c^\beta\bar{p}_{jc}^{\beta(\alpha_t-1)}$$

Then,

$$\begin{aligned}V_j =&\left(\sum_k\left(A_k\tilde{B}_k\bar{p}_{jk}^{(\alpha_t-1)}\right)^{\frac{\beta}{\lambda}}\right)^\lambda\\ V_N =&\left(\sum_k\left(A_k\tilde{B}_k p_k^{(\alpha_t-1)}\right)^{\frac{\beta}{\lambda}}\right)^\lambda=\left(\sum_k\left(\frac{A_k\tilde{B}_k}{p_c^{1-\alpha_t}}\right)^{\frac{\beta}{\lambda}}\right)^\lambda\end{aligned}$$

In equilibrium, $p_c = L_c^{\eta_c}$. Thus,

$$\ln V_j - \ln V_N = -\lambda \ln \frac{\sum_k \left(A_k \tilde{B}_k / L_k^{\eta_k(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}{\sum_k \left(A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}$$

Hence,

$$\ln \frac{\pi_{jc}}{\pi_{Nc}} = \frac{1}{\lambda}\left(\beta(1-\alpha_t)\ln p_c - \beta(1-\alpha_t)\ln \bar{p}_{jc}\right) + \ln \frac{\sum_k \left(A_k \tilde{B}_k / L_k^{\eta_k(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}{\sum_k \left(A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}$$

Denote $M = \ln \frac{\pi_{jc}}{\pi_{Nc}}$. Then,

$$\begin{aligned}\frac{\partial M}{\partial p_c} =& \frac{1}{\lambda}\left(\frac{\beta(1-\alpha_t)}{p_c} - \frac{\beta(1-\alpha_t)\bar{\alpha}_l^{\sigma} p_c^{-\sigma}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}\right) \\ =& \frac{\beta(1-\alpha_t)}{\lambda} \frac{\frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}} > 0\end{aligned}$$

This tells us that the distribution of immigrants relative to natives is higher in more expensive cities.

□

Proof. **Proposition 3**

Note

$$\pi_{jc} = \frac{L_{jc}}{L_j} = \left(\frac{V_{jc}}{V_j}\right)^{\frac{1}{\lambda}} = \left(\frac{A_c^{\beta}\tilde{B}_c^{\beta}/\bar{p}_{jc}^{\beta(1-\alpha_t)}}{V_j}\right)^{\frac{1}{\lambda}}$$

Then, the total immigrant population in city c is

$$L_{Ic} = \sum_j L_{jc} = \sum_j L_j \frac{L_{jc}}{L_j} = \sum_j L_j \left(\frac{A_c^{\beta}\tilde{B}_c^{\beta}/\bar{p}_{jc}^{\beta(1-\alpha_t)}}{V_j}\right)^{\frac{1}{\lambda}}$$

Substituting the expression for V_j, we get

$$L_{Ic} = (A_c\tilde{B}_c)^{\frac{\beta}{\lambda}} \sum_j \frac{L_j/\bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k\tilde{B}_k/\bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}}$$

For natives,

$$L_{Nc} = \frac{(A_c\tilde{B}_c)^{\frac{\beta}{\lambda}}}{\sum_k (A_k\tilde{B}_k/p_k^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} L_N / p_c^{(1-\alpha_t)\frac{\beta}{\lambda}} = \frac{(A_c\tilde{B}_c/L_c^{\eta_c\alpha})^{\frac{\beta}{\lambda}}}{\sum_k (A_k\tilde{B}_k/L_k^{\eta_k\alpha})^{\frac{\beta}{\lambda}}} L_N$$

And $L_c = L_{Ic} + L_{Nc}$. □

Proof. **Proposition 4**

Note

$$q = \sum_c \frac{B_c L_c}{L}$$

Thus,

$$q = \sum_c \left[(A_c \tilde{B}_c^{\frac{\beta+\lambda}{\beta}})^{\frac{\beta}{\lambda}} \sum_j \frac{\frac{L_j}{L} / \bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} \right] + \frac{\sum_c (A_c \tilde{B}_c^{\frac{\beta+\lambda}{\beta}} / L_c^{\eta_c \alpha})^{\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / L_k^{\eta_k \alpha})^{\frac{\beta}{\lambda}}} \frac{L_N}{L}$$

□

B Supplementary evidence

B.1 Robustness to alternative hypotheses

In this subsection, we investigate a number of alternative hypotheses that can either reinforce our results or potentially explain them. As we show in this section, alternative stories cannot explain the patterns in the data that we document. Moreover, we show that for groups of immigrants that are probably less attached to their home countries, these results are attenuated.

Immigration longevity in the US

According to Dustmann and Mestres (2010), immigrants that do not intend to return to their countries of origin remit a smaller share of their income. They are also less likely to spend time back home and thus are, in some way, more similar to natives. There is also a large body of literature starting with Chiswick (1978) that estimates the speed of assimilation into the receiving country. This literature has interpreted the early gap in wages between natives and immigrants as the lack of skills specific to the receiving country. While this is certainly a possibility, it does not explain why this gap is increasing in city size. However, we can use the insights from the immigrant assimilation literature to see whether the relationship between city size and city price level is stronger for newly arrived immigrants than for older ones. For this, we use the year of immigration taken from the Census data and divide immigrants into groups depending on their time spent in the US.

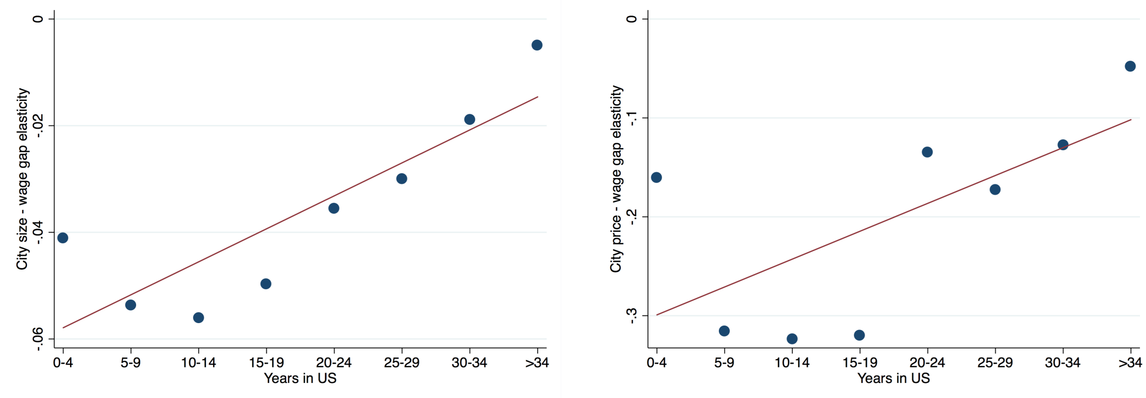
We plot the coefficients for different groups of immigrants by the years since arrival in Figure B.1. This shows that the elasticities are weaker for immigrants that have lived in the US for longer. The relationships between wage-gap elasticity and longevity seem to be non-linear for both city size and city price, initially becoming stronger with a peak for immigrants that have spent 10-14 years in the US and declining subsequently. A possible explanation for this is that the origin composition of immigrants varies depending on longevity, e.g. there is a disproportionately high number of recently arrived immigrants from countries with price levels similar to the US. If we repeat the estimation without immigrants from these countries, for whom we expect an elasticity of close to zero independently of longevity (see Fact 4), the relationships in Figure B.1 become more linear.[42] In particular, the estimates of the elasticity for immigrants that have spent 0-4 years in the US drop to around -0.05 in the left-hand plot and -0.3 in the right-hand plot, while the remaining estimates change little.

Immigrant networks

The results shown in the main text strongly suggest that immigrants earn less than natives in more expensive cities. In this paper, we argue that this is related to immigrants' share of consumption in their countries of origin. An alternative would be that immigrants earn less in large cities because there are large immigrant communities there. If immigrants perceive communities of their country of origin as a positive amenity, they could potentially accept lower wages in large, expensive cities because they are compensated through immigrant-network amenities. If this were the only mechanism at play, we would

[42]We exclude immigrants from Europe, Canada, Australia, New Zealand, Japan, and South Korea.

Figure B.1: City size/price elasticity of wage gap by immigrant longevity



Notes: This figure uses data from the Census 2000 to show the relationships between the city size and city price elasticity of the native-immigrant wage gap depending on time spent in the US. Each dot represents an estimate of the coefficient β for the particular group based on Equation 3.3.

expect the relationship between wage gaps and city size to become stronger over time–which we do not see–but it is still worth investigating the importance of migrant networks in greater depth.

To investigate this alternative, we extend the basic regression framework introduced in Equation 3.3 to compute the estimates shown in Figures 5 and 6 to incorporate immigrant networks. Specifically, we estimate:

$$\begin{aligned}\ln w_{i,c,t} = & \alpha_{1t} + \alpha_{2t} Imm_{i,c,t} + \beta_1 Imm_{i,c,t} * \ln Pop_{c,t} \\ & + \gamma_1 \ln Pop_{c,t} + \beta_2 ImmigNetwork_{i,c,t} \\ & + \gamma_1 ImmigNetwork_{i,c,t} * \ln Pop_{c,t} + \phi X_{i,c,t} + \delta_{ct} + \varepsilon_{i,c,t}\end{aligned} \tag{B.1}$$

where we measure the size of the network as $ImmigNetwork_{i,c,t} = \frac{Pop(i)_{c,t}}{Pop_{c,t}}$. That is, for each individual i, we compute the number of individuals from the same country of origin that at time t live in city c. For natives, this measure of immigrant networks takes a value of 0. Thus, β_2 measures the relative wages of immigrants and natives, given the various sizes of the network, while β_1 measures whether there is still a negative premium for immigrants in large cities, conditional on the role of migration networks.

Table B.1 shows the results. In Column 1, we only include the size of the migration network. As suggested in Borjas (2015), migrant networks may be detrimental to immigrant wages. Our estimates suggest that a network that is 1 percent larger is associated with wages that are almost 1 percent lower. This negative relationship can be interpreted as evidence that immigrant networks are detrimental to immigrant assimilation into the labor market, or to the fact that migrant networks may be a positive amenity for immigrants, and thus, when living in larger networks, immigrants may be willing to work for a lower wage. In Column 2, we investigate whether the size of the network is more or less important in large cities. As the results show, it seems that immigrant networks are associated with lower immigrant wages, especially in larger cities.[43] In Column 3, we replicate the results already shown: immigrants'

[43] Note that the total effect of migrant networks on immigrants' wages in Column 2 is positive if the MSA population is above around 22,000. According to Column 3, immigrants have a lower wage than natives if the MSA population is above around 8,000. The population levels of all MSAs in our sample are above these thresholds at any point in time.

Table B.1: Wage gaps and immigrant networks

VARIABLES	(1) Wage OLS	(2) Wage OLS	(3) Wage OLS	(4) Wage OLS	(5) Wage OLS
Migrant network x (ln) Population in MSA		-0.252***			-0.0944**
		(0.0699)			(0.0384)
Migrant network in MSA	-0.976***	2.522***		-0.451***	0.865*
	(0.0802)	(0.884)		(0.0403)	(0.496)
(ln) Population in MSA	0.0306***	0.0342***	0.0423***	0.0397***	0.0399***
	(0.0117)	(0.0120)	(0.0156)	(0.0133)	(0.0132)
Immigrant			0.278***	0.356***	0.266***
			(0.102)	(0.0619)	(0.0731)
(ln) Population in MSA x Immigrant			-0.0310***	-0.0347***	-0.0283***
			(0.00770)	(0.00461)	(0.00548)
Observations	360,970	360,970	360,970	360,970	360,970
R-squared	0.413	0.414	0.417	0.418	0.418
Xs	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
MSA FE	yes	yes	yes	yes	yes

Notes: This table shows estimates of the native-immigrant wage gap and how it changes with city size, controlling for immigration networks. Immigration networks are measured as the relative size of the immigrant population of each different country of origin with respect to the host metropolitan area. GDP origin is GDP per capita in the country of origin. These estimates use CPS data from 1994 to 2011.

wages are lower than natives', especially in large cities. Columns 4 and 5 show that this negative premium of immigrants in large cities remains even when we control for immigration networks. In Column 4, we include in our baseline regression a control for the size of the network, while in Column 5 we also include the interaction of the size of the network and city size. In neither of these cases do these controls change our estimate of the relative wage gap between immigrants and natives, and city size.

Something that is potentially related to immigration networks and that may also help explain our results is the fact that the rate of learning may vary with city size (see the important work by de la Roca and Puga (2017)): perhaps wage gaps are greater in large cities because it takes time to learn the skills necessary to thrive there. If immigrants stayed in large cities for less time, this could generate the wage gap results that we obtain. To investigate this, we extend our baseline regression by including the (ln) years that immigrants have spent in the US and the interaction of this with city size. As shown in Column 5 in Table C.1 in Appendix C.1, this does not explain our results either.

Thus, while immigrant networks seem to play a role in determining wage levels, it does not seem that they can account for the patterns in the data that we described above.

Immigrants' human capital and immigrant-native substitutability

A potential alternative story that could explain why the average immigrant-native wage gap is higher in larger cities may be that immigrants with lower levels of human capital concentrate there, at least relative to natives. To investigate this further, we separate our sample of immigrants and natives into four education groups and investigate whether within these education groups we obtain the same immigrant-native wage gaps that we have documented. Table B.2 reports these results. The interaction of city size and the immigrant dummy that identifies the elasticity of native-immigrant wage gaps and city size

Table B.2: Immigrant-native wage gaps and human capital

VARIABLES	(1) Wage All	(2) Wage <HS	(3) Wage HS	(4) Wage SC	(5) Wage C
Immigrant	0.262*	0.115	0.239*	0.328***	0.186*
	(0.144)	(0.0765)	(0.128)	(0.0978)	(0.104)
(ln) Population in MSA	0.0438***	0.0371	0.0200	0.0338*	0.0644***
	(0.0167)	(0.0262)	(0.0235)	(0.0179)	(0.0180)
(ln) Population in MSA x Immigrant	-0.0337***	-0.0186***	-0.0305***	-0.0346***	-0.0201***
	(0.0110)	(0.00544)	(0.00949)	(0.00726)	(0.00745)
Observations	360,970	39,537	101,885	94,124	125,424
R-squared	0.382	0.224	0.262	0.269	0.310
Xs	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
MSA FE	yes	yes	yes	yes	yes

Notes: These regressions report only selected coefficients. The complete set of explanatory variables is specified in Equation 3.3. Columns 2 to 5 show results by education group (high school dropout, high school graduate, some college, college). Column 1 shows the entire sample. Robust standard errors, clustered at the metropolitan area level, are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.

fluctuates from around 2 percent to around 3.5 percent for all education groups, even after controlling for other observable characteristics. Thus, the results reported so far suggest that there is a mechanism that is independent of human capital levels.

An alternative explanation of these results is that immigrants and natives are imperfect substitutes (Ottaviano and Peri, 2012; Manacorda et al., 2012). This would generate a negative relationship between native-immigrant wage gaps and the number of immigrants (relative to natives) in a location. It is not clear why immigrants, in this alternative story, systematically cluster in larger, more expensive cities, but there could be an unknown factor that accounts for this. In order to investigate whether this is what is driving our results, we use Equation B.1 but substitute the "migration network" variable by the share of immigrants within each education group in each metropolitan area.[44]

Table B.3 shows that when controlling for the relative supply of immigrants within education, we obtain the same relationship between immigrant-native wage gaps as with our baseline estimates. Column 1 in Table B.3 shows that there is a negative relationship between wage gaps and immigrant shares. This is consistent with immigrants and natives being imperfect substitutes within narrowly defined education groups. In Column 2, we show that this relationship seems to be stronger in larger cities, something that may explain our baseline results, shown in Column 3 for convenience. Columns 4 and 5 show that this is not the case. The interaction of the immigrant identifier and city size is unchanged by the inclusion of the share of immigrants in the metropolitan area within education groups, and, if anything, this regression suggests that an important part of the role that previous papers have attributed to imperfect native-immigrant substitutability may in fact be explained by immigrants' endogenous location choice.

[44] Alternatively, we can use the share of immigrants in the metropolitan area. This usually results in smaller estimates. See discussions in Card (2001), Borjas (2003), Card (2009), Borjas and Monras (2017), and Dustmann et al. (2016).

Table B.3: Wage gaps and imperfect native-immigrant substitutability

VARIABLES	(1) Wage OLS	(2) Wage OLS	(3) Wage OLS	(4) Wage OLS	(5) Wage OLS
Share of immigrants (by edcode) x (ln) Population in MSA		-0.0763***			-0.0386***
		(0.0106)			(0.00842)
Share of immigrants (by edcode)	-0.249***	0.805***		-0.108***	0.427***
	(0.0384)	(0.137)		(0.0260)	(0.114)
(ln) Population in MSA	0.0360***	0.0500***	0.0423***	0.0416***	0.0478***
	(0.0128)	(0.0149)	(0.0156)	(0.0137)	(0.0145)
Immigrant			0.278***	0.302***	0.226**
			(0.102)	(0.0982)	(0.0913)
(ln) Population in MSA x Immigrant			-0.0310***	-0.0323***	-0.0270***
			(0.00770)	(0.00735)	(0.00685)
Observations	360,970	360,970	360,970	360,970	360,970
R-squared	0.411	0.411	0.417	0.418	0.418
Xs	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
MSA FE	yes	yes	yes	yes	yes

Notes: This table shows estimates of the native-immigrant wage gap and how it changes with city size, controlling for immigrant supply. Immigrant supply shocks are measured as the relative size of the immigrant population in each metropolitan area and each of the four education codes previously reported. These estimates use CPS data from 1994 to 2011.

B.2 price indices and city size

In this subsection, we show that city size and city price indices are strongly correlated in the data. We emphasize throughout the text that we obtain similar results when using city size or city price levels to differentiate the metropolitan areas. These two measures are indeed strongly correlated, as can be seen in Figure B.2. In fact, the relationship becomes steeper over time.

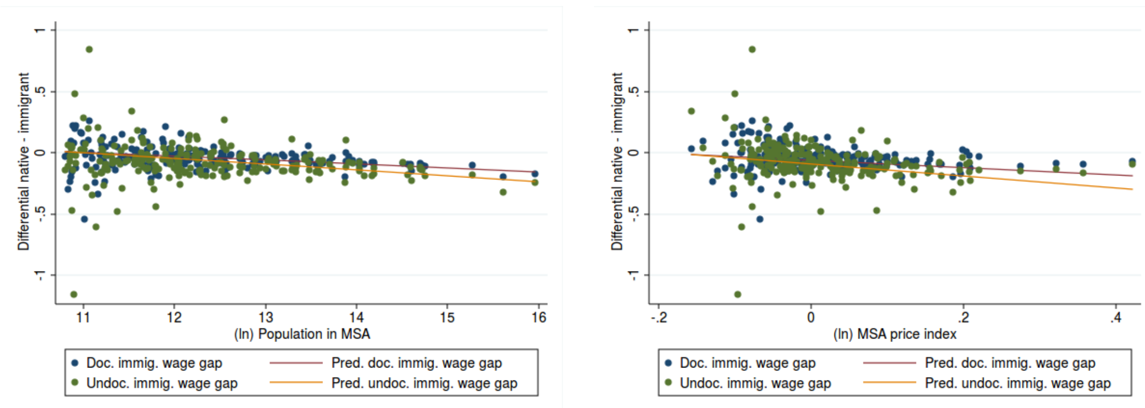
Figure B.2: City size and price index

Notes: MSA populations are based on the sample of prime-age workers (25-59) from the Census 2000. The MSA price indices are computed following Moretti (2013). Each dot represents a different MSA-year combination. We have 219 different metropolitan areas in our sample.

B.3 Undocumented immigrants

In this subsection, we show that the wage results are not a consequence of undocumented workers. For this, we show that we obtain similar relationships between wage levels and city sizes and prices when we restrict the analysis to documented and to undocumented immigrants. We identify undocumented immigrants following Borjas (Forthcoming).

Figure B.3: Wage gaps, city size, and price indices (Census 2000)



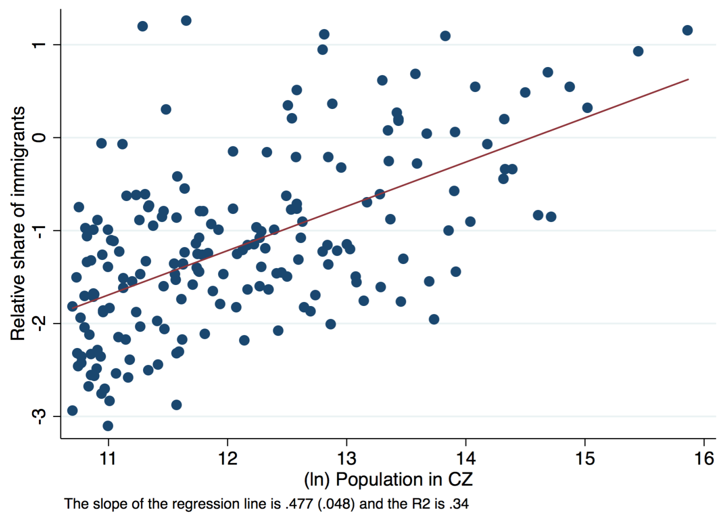
Notes: This figure uses data from the Census 2000 to show the relationship between the wage gaps of documented and undocumented immigrants to natives, city sizes, and prices. Each dot represents one of the 219 different metropolitan areas in our sample.

B.4 Commuting zones

This section shows that the main relationship between relative location choices and relative wages between natives and immigrants documented throughout the paper is independent of using metropolitan-area-level data or commuting zone data. While in our context it seems quite natural to think about metropolitan areas, some papers have emphasized the use of local labor markets which are typically measured by commuting zones. In our context, metropolitan areas may be a more natural unit of observation because in the monocentric city, Von-Thunen model we can think of a unique house-price index within them, something that is perhaps less natural for commuting zones (Von Thunen, 1826).

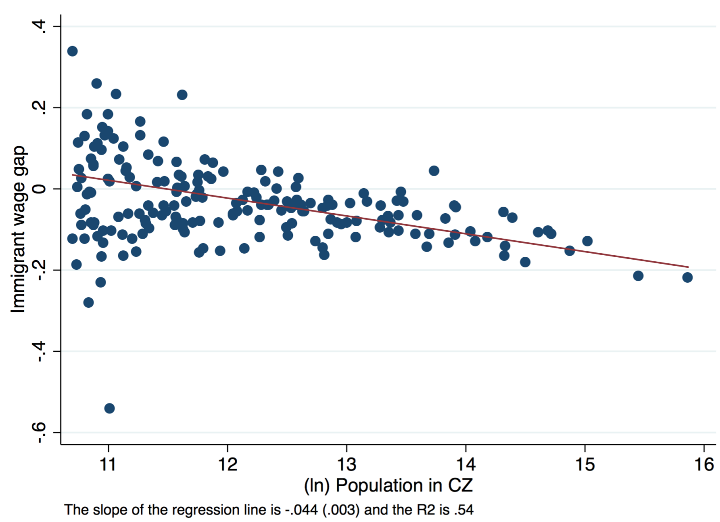
It is, however, worth checking that at least the main results reported in the paper do not depend in the geographic unit of analysis. Figures B.4 and B.5 show that immigrants concentrate in large commuting zones and their wages relative to natives are lower there. All other results that we have checked are unchanged when using commuting zones instead of metropolitan areas.

Figure B.4: Commuting zone size and immigrant distribution



Notes: The figure is based on the sample of prime-age workers (25-59) from the Census 2000. Each dot represents a different commuting zone. There are 191 different commuting zones in our sample. The red line is the fitted line of a linear regression.

Figure B.5: Commuting zone size and wage gaps



Notes: This figure uses data from the Census 2000 to show the relationship between native-immigrant wage gaps and city sizes and prices. Each dot represents the gap in earnings between immigrants and natives in a commuting zone. There are 191 different commuting zones in our sample. The red line is the fitted line of a linear regression.

C Regression tables

In this section, we present the regression tables mentioned in the main text.

C.1 Baseline wage regression

Table C.1: Baseline wage regression

VARIABLES	(1) Wage OLS	(2) Wage OLS	(3) Wage OLS	(4) Wage OLS	(5) Wage OLS
Immigrant	0.318	0.323**	0.320**	0.278***	0.344
	(0.249)	(0.144)	(0.145)	(0.102)	(0.256)
(ln) Population in MSA	0.0597***	0.0446***	0.0446***	0.0423***	0.0462***
	(0.00463)	(0.00308)	(0.00308)	(0.0156)	(0.0157)
(ln) Population in MSA x Immigrant	-0.0474**	-0.0340***	-0.0338***	-0.0310***	-0.0480**
	(0.0183)	(0.0106)	(0.0107)	(0.00770)	(0.0191)
Observations	360,970	360,970	360,970	360,970	356,143
R-squared	0.051	0.407	0.408	0.417	0.416
Xs	no	yes	yes	yes	yes + learn
Year FE	no	no	yes	yes	yes
MSA FE	no	no	no	yes	yes

Notes: Regressions are based on a CPS sample including male prime-age salaried workers (25-59). These regressions report only selected coefficients. The complete set of explanatory variables is specified in Equation 3.3. In Column 5, we include (ln) year in the US and its interaction with city size. We lose a few observations in this column because of lack of data and misrecording of the variable in CPS data. Robust standard errors, clustered at the metropolitan area level, are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.