Immigration and the Pursuit of Amenities

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Abstract

Immigrants to the United States live disproportionately in metropolitan areas where nominal wages are high, but real wages are low. This sorting behavior may be due to preferences toward certain quality-of-life amenities. Relative to U.S.-born inter-state migrants, immigrants accept lower real wages to locate in cities that are coastal, larger, and offer deeper immigrant networks. They sort towards cities that are hillier and also larger and networked. Immigrants come more from coastal, cloudy, and safer countries – conditional on income and distance. They choose cities that resemble their origin in terms of winter temperature, safety, and coastal proximity.

JEL Codes: J15, J61, Q51, R23

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1. INTRODUCTION

Economists who study international migration naturally focus on labor markets and moves that raise income. Yet, economists who study domestic migration often consider how workers pursue amenities as well as income — e.g. Roback (1982), Albouy (2008), and Diamond (2016). Amenity-induced moves may lower income, yet still improve well-being by raising households' quality of life.

Here, we examine whether amenities affect the location of immigrants within the United States. Pre-existing research has documented how immigrants select metropolitan areas with high nominal wages (Borjas, 2001) and with deeper immigrant networks, or "enclaves," where their predecessors went (Card and Dinardo, 2000, Saiz, 2007). Instead, we consider how amenities affect the real wages immigrants earn, as amenable areas often have high costs-of-living that lower real wages. Many amenities are natural, such as warmth or hilliness, and are essentially fixed over time. Therefore, immigrant enclaves may themselves result from the continued attraction of some amenities.

Accordingly, we examine whether immigrants are drawn to different kinds of amenities than natives. Such differences might arise from differences in preferences, although explaining differential behavior simply with preferences is generally unappealing scientifically (Stigler and Becker, 1977). However, since immigrants hail from different countries, these apparent differences in preferences may arise naturally from habit. Just as individuals have path-dependent tastes for certain foods, such as for spice, the same may be true for climate, such as for heat. An immigrant who adopts unfamiliar amenities may bear psychic costs similar to one being forced to eat an unfamiliar diet. Thus, to lower their costs of adapting to their new environment, immigrants may pursue amenities in their destination cities similar to that of their country of origin. On the other hand, some immigrants may leave their home country precisely to pursue amenities that differ from the ones at home.

The evidence presented is largely descriptive, and therefore we cannot make strong claims as to whether amenities truly cause immigrants to choose one location relative to another. Nonetheless, we do document several findings that may deserve greater attention. First, immigrants live disproportionately in metropolitan areas where real wages are low, even though their nominal wages are high. These areas have low real wages because of especially high costs of living. In contrast, native-born migrants — who live in a different state than they were born in — go to places with both low nominal and real wages.

Second, immigrants are willing to take lower real wages — i.e., pay more — to live in areas with pre-existing enclaves of immigrants. In particular, they are drawn to enclaves that represent countries from which immigration is currently strong. This finding is consistent with the idea that existing immigrant networks are an amenity to new immigrants. Otherwise, immigrants and natives show similar willingness to pay (WTP) to be in the same metro areas, with some exceptions. Immigrants sacrifice slightly more to be in cities that are larger and more coastal. Within those cities, they seem to live in cheaper neighborhoods. Immigrants' location choices relative to native-born migrants, i.e., their differential "sorting", is arguably more revealing. Immigrants sort more towards cities with sun, hills, high population, low education, near ports of entry, and which have heavier land-use regulations. On the other hand, native migrants — relative to native non-movers — sort towards metros that are warm, non-coastal, small, and more educated. For example, immigrants go towards cities like Los Angeles, CA, while natives move towards cities like Fort Collins, CO.

How non-market amenities determine international migration has received little attention to our knowledge. Researchers have mostly examined how immigration may be affected by climate change — e.g., Black et al. (2011) and Missirain and Schlenker (2017). Yet, there are no studies that examine how level differences in climate — or other amenities — determine international migration. This is surprising as it seems like a natural complement to the existing literature. Nor has any study attempted to link amenities in immigrants' locations within the U.S. and their country of origin. Indeed, understanding how international migration is affected by level differences in climate amenities may be necessary for understanding how it is affected by changes.

2. WILLINGNESS TO PAY, SORTING, AND AMENITIES

A spatial equilibrium model can rationalize how immigrants and natives choose where to live. We use a model with two worker types, e.g., Roback (1988), Albouy (2013), and Moretti (2013). Workers reveal the amenities they prioritize through how frequently they choose, or sort to, a city. This follows the spirit of spatial selection models such as McFadden (1978), Bayer et al. (2007), Gyourko et al. (2013). They also reveal them through how much they pay, or "sacrifice", to live in a city. This sacrifice may take the form of paying higher rents or receiving lower wages, or both (Rosen, 1979, Roback, 1982, Albouy, 2008).

2.1. Willingness-to-Pay and Productivity in Spatial Equilibrium

Consider a population of households that must choose a city j to live and work. In that city, a household must buy traded and local goods, where the latter have a price p_j that differs across space, such as housing costs and restaurant prices. Labor markets also offer different wage levels w_j, which may compensate them for higher prices or fewer amenities. In each city j, households' willingess to pay for those amenities is then given by how high local prices are relative to after-tax income:

$$W\hat{T}P_j = s_p\hat{p}_j - (1-\tau)s_w\hat{w}_j \tag{1}$$

This uses log deviations from the national average, expressed with the hat notation $\hat{x}_j = \ln(\frac{x_j}{\bar{x}}) = dx_j/\bar{x}$, where $\bar{x}$ is the national average.[1] The weights on prices and wages, s_p and s_w, are the share of income spent on local goods and the share of income from labor. The marginal tax rate on labor earnings is τ.

When households are perfectly mobile and have similar tastes, the $W\hat{T}P_j$ alone an be used to estimate how households value amenities. If two cities are occupied, it is because households are indifferent between them: any differences in real income must be compensated for by amenities, and vice versa. Any imbalance would cause households to move towards the better city until the two became equal again, or the worse city empties out.

A second determinant of location are productivity levels. We keep things simple by using a single measure of "trade-productivity", $\hat{A}_j^Y$. This essentially measures firms' willingness to pay. Firms in more productive cities pay more in wages and land costs, thus this is measured by a weighted average of wages and land costs inferred from residential housing. It is critical in modeling how wages and housing costs move in similar directions, while quality-of-life amenities push them in opposite directions. As covered in Albouy (2016), trade-productivity is estimated as $\hat{A}_j^Y = 0.11\hat{p}_j + 0.76\hat{w}_j$, according to cost shares in traded and housing production.

2.2. Household Sorting with a Simple Friction

The sorting argument rests on the idea that the number of households choosing one city over another provides information about the value of a city's amenities. To model this, researchers assume that households have idiosyncratic tastes for each city that have a smooth random distribution. This model implies that the more households prefer city 1 over city 2, the greater the number of households we should see in city 1 relative to city 2. This ratio is

[1]This comes from the approximation of log expression around the national geometric average using Taylor series: $\ln(\frac{x_j}{\bar{x}}) = \frac{x_j - \bar{x}}{\bar{x}}$.

rarely infinite, because someone in city 2 has a particular reason for staying there, even if wages or amenities would otherwise bring them to city 1.

Allowing for these idiosyncratic tastes for cities requires adding a quantity measure, N, to the price measures in the $W\hat{T}P_j$. Based on a simplified version of a discrete choice model, we infer that the value of amenities in a place — i.e., the quality of life it offers, denoted by $\hat{Q}_j$ — is given by the willingness-to-pay measure plus a term for how much more population we see relative to the average.

$$\hat{Q}_j = s_p \hat{p}_j - (1-\tau) s_w \hat{w}_j + \psi \hat{N}_j \tag{2a}$$

$$= W\hat{T}P_j + \psi \hat{N}_j \tag{2b}$$

The parameter ψ determines how much sorting behavior reveals tastes for amenities relative to willingness to pay. It is based on just how heterogeneous idiosyncratic tastes are: the more heterogeneous, the higher ψ. If one solves for $\hat{N}_j$, this expression also gives a downward sloping demand curve to live in city j, $\hat{N}_j = \left(\hat{Q}_j - W\hat{T}P_j\right)/\psi$, where the slope of the curve is given by ψ.

Unfortunately, the parameter ψ cannot be observed directly, but must be estimated or calibrated. With the proper weights on relative prices, wages and population, one could then infer in principle how much households are willing to pay for different amenities on the margin. Like with other city-level wage and housing-price equations, this technique is subject to problems with omitted variables, specification errors, and simultaneity issues.[2]

[2]See Gyourko et al. (2008), Albouy (2016). Country-specific fixed effects can control for time-invariant characteristics of country of origins, but they cannot generally solve the above problem. Thus, the estimates here should not be interpreted causally.

2.3. How Immigrants and Natives Reveal Preferences Differently

Our subject of interest here has more to do with how immigrants value amenities differently from natives, and less with how they value amenities absolutely. To model relative valuations, let the superscript I denote variables for immigrants, and B for native-born. If the two groups have different preferences for amenities, they can receive different quality-of-life benefits in each city. According to our two measures, the quality of life received by immigrants relative to natives should be reflected by differences in willingness to pay and in sorting:

$$\hat{Q}_j^I - \hat{Q}_j^B = W\hat{T}P_j^I - W\hat{T}P_j^B + \psi^I \hat{N}_j^I - \psi^B \hat{N}_j^B \tag{3a}$$

$$\begin{aligned} &= s_p^I \left(\hat{p}_j^I - \hat{p}_j^B\right) + \left(s_p^I - s_p^B\right) \hat{p}_j^B \\ &- (1-\tau^I) s_w^I \left(\hat{w}_j^I - \hat{w}_j^B\right) - \left[(1-\tau^I)s_w^I - (1-\tau^B)s_w^B\right] \hat{w}_j^B \\ &+ \psi^I \left(\hat{N}_j^I - \hat{N}_j^B\right) + \left(\psi^I - \psi^B\right) \hat{N}_j^B \end{aligned} \tag{3b}$$

The latter part of the equation breaks apart the the sub-components of the willingness-to-pay measure in (3a) into its constituent data. First, (3b) contains differences in local good prices $\hat{p}_j^I - \hat{p}_j^B$. This may come from immigrant residential segregation or landlord discrimination. Second, immigrants may have stronger or weaker tastes for the local good, reflected in different expenditure shares $s_p^I - s_p^B$. Stronger tastes would mean putting greater weight on local housing costs.

Wage differences $\hat{w}_j^I - \hat{w}_j^B$ in (3b) could come from unobserved skill differences: e.g., English proficiency, the return to which could vary across cities. It could also arise from employer discrimination. Differences in net of tax wage share of income $(1-\tau^I)s_w^I - (1-\tau^B)s_w^B$ also determine the weight put on wages. Households that have less non-labor income will be more dependent and more drawn to high-wage areas.

Finally, population differences $\hat{N}_j^I - \hat{N}_j^B$ in (3b) reflect differential sorting behavior. Its importance relative to willingness to pay depends critically on the idiosyncratic preference heterogeneity parameter ψ. However, since ψ is not observed directly, and its estimates vary widely in the literature, we remain agnostic about its value. Instead, we examine differences in sorting separately from differences in willingness to pay, acknowledging that both are signals of quality-of-life amenities.

The last term $\left(\psi^I - \psi^B\right)\hat{N}_j^B$ results from differences in the heterogeneity parameter. For simplicity, we ignore this term, partly because it is difficult to interpret absolute differences in population $\hat{N}_j^B$ across metropolitan areas. Also, evidence presented by Diamond (2016) suggests that the preference heterogeneity parameters may be the same i.e., $\psi^I = \psi^B$.[3]

Of course, tastes for particular amenities may also differ for immigrants. To formalize this, suppose that the overall quality of life derived for particular amenities Z_{ja}, where a indexes amenities, is determined by a linear model:

$$\hat{Q}_j^I = \sum_a \pi_a^I Z_{ja} + \eta_j^I \tag{4a}$$

$$\hat{Q}_j^B = \sum_a \pi_a^B Z_{ja} + \eta_j^B \tag{4b}$$

The coefficients π_a^I and π_a^B give how much immigrants and natives value amenity Z_{ja} as a fraction of their real income. As we consider below, when immigrants value amenities more than natives, $\pi_a^I > \pi_a^B$, we may see this in both willingness-to-pay and sorting differences.[4]

[3]If immigrants are more mobile than natives, $\psi^I < \psi^B$, then we expect to see immigrants to sort more strongly than natives even with the same preferences for amenities. Similar levels of sorting would imply that natives incurred greater moving costs than immigrants, and therefore value the amenity more.

[4]Note that there may be vastly more types, depending on the specific country of origin. The most straightforward way to test for heterogeneity in preferences is to divide immigrants into groups by the country of origin. If preferences are correlated with amenities in the country of origin, immigrants may sort into cities with similar natural amenities (for example, people from warm places may prefer cities with mild winters and can tolerate hot summers). This could reduce adaptation costs of moving. The other possibility is that immigrants may seek ways to escape from unfavorable environment in the county of origin. We test this,

There are several reasons why immigrants and natives may value amenities differently. Habits formed in the country of origin, mentioned above, is one. The World Values Survey documents differences by country in how respondents value (for example) leisure time, work, religion, and environmental protection (Inglehart et al., 2014). Another reason is self-selection: individuals who have certain traits are more likely to migrate in the first place — for example, they may be more willing to take risks (Jaeger et al., 2010). Immigrants and natives may also differ in cognitive and non-cognitive traits, such as their planning horizon and perceived constraints (Luik and Steinhardt, 2016).

2.4. The Implicit Role of Amenities in Previous Research

Since immigrants are born abroad, they should have fewer ties to any particular domestic location than a native. As they have already sunk fixed costs of moving, Borjas (2001) argues that immigrants will seek out labor markets with the highest wages. Indeed, he argues that immigrants reduce inter-regional wage differences of similarly-skilled workers across cities. In a more general model, the argument extends to markets offering the best amenities as well as wages.

Borjas' findings are at odds with Card (2001), who finds that immigrants exert only small downward pressure on wages. Card uses immigrant enclaves as an instrumental variable for immigrant supply. According to Card and Dinardo (2000), higher immigration levels do not result in native outflows either. However, Saiz (2007), using a similar methodology, finds that immigrants put upward pressure on housing rents. All of these studies use immigrant enclaves to predict where future immigrants will land, based on how previous immigrant have sorted.[5]

In terms of our spatial model, if immigrants sort to areas where they have strong social

interacting amenities in the country of origin and in the receiving city.

[5]The implicit assumption in using immigrants as an instrument for labor supply is that previous immigrants offer non-market benefits to immigrants from the same country, as disscussed in Section 3.5.

networks, previous immigrants might be seen as amenity to newer immigrants. This introduces a new prediction that has not been tested: the willingness to pay of immigrants should be greater in places with existing enclaves. Moreover, the exclusion restriction needed to use enclaves as an instrument for labor supply requires that the social networks created by enclaves do not affect immigrants' labor productivity.

Taken together, the Card and Saiz papers imply that workers — by accepting higher prices without getting more in wages — recieve lower real wages in areas where the supply of immigrants has grown the most. Furthermore, these places see population growth. In a spatial equilibrium with perfect mobility, real wages can fall as population grows only if quality of life rises. However, that ceases to be true if friction to mobility — respresented by the ψ paramters — are large enough. If labor mobility is low, real wages can fall without quality of life improving. Workers in immigrant-receiving cities may simply accept lower real wages because of their ties to the area, and be made worse off.

If quality of life in immigrant-receiving areas does rise, it would be interesting to know if immigrant simply went to places where quality of life grew, or if growing immigration itself caused local quality of life to rise.[6]

3. DATA AND MEASUREMENT

3.1. Household Data

We estimate wage and housing cost differentials for 2000 and 2014 separately, using the Integrated Public Use Microdata Series (Ruggles et al., 2017) 5 percent sample of the 2000

[6]An issue we do not address is how immigrants might change local amenities. For instance, immigrant could have positive effects by enriching local culture or changing neighborhoods in ways natives value less Saiz and Wachter (2007). Some have examined possible impacts on crime Bell and Machin (2013). Others have considered whether immigrants put stress on local public service provision, such as schools, e.g. Hunt (2016).

Census (Long Form) and the pooled 2012-2016 American Community Survey, i.e., the "2014" sample. Our 276 "cities" in the 2000 and 2014 samples are based on 1999 OMB definitions of metropolitan statistical areas (MSAs).[7] We focus on metropolitan areas as they not only describe a typical labor market, but also can be thought to share many common amenities.

In accordance with the model, we derive wage and price differentials of each metro area for immigrants and natives separately. For wages, we use an individual-level regression of the logarithm of hourly wages, controlling for workers' characteristics:

$$\ln w_{ij} = X_i^w \beta + \hat{w}_j + \epsilon_{ij}^w \tag{5}$$

This controls for a broad set of individual-level characteristics X_i^w, including education and experience. The inferred wage differential in the city j is the fixed-effect coefficient $\hat{w}_j$.[8] This wage differential is re-centered in a way that it reflects the group-specific (immigrants, natives or native migrants) log deviation from the national average for all groups. For example, $\hat{w}_j{}^I = \ln w_j{}^I - \ln \bar{w}$ is the wage differential for immigrants in metro j, where $\bar{w}$ is the national geometric average wage for everyone.

Similarly, housing-cost differentials are calculated using a household-level regression of gross rents (imputed rents for owner-occupied units) on dwelling characteristics:

$$\ln p_{ij} = X_i^p \beta + \hat{p}_j + \epsilon_{ij}^p \tag{6}$$

[7]We use the MABLE/Geocorr2K Geographic Correspondence Engine (MABLE/Geocorr14 for 2010 Census geography) to consistently define MSAs. This is an online application that generates custom geographical crosswalks. Using this tool, we match 2014 and 2000 Census data to 1999 OMB delineations of MSAs.

[8]The full list of individual-level controls includes education, experience, interaction of education and experience, marital status, race and ethnicity, veteran status, industry, occupation, and ability to speak English, all interacted with the female indicator. As is standard, potential experience is defined as age minus years of schooling minus 5. Then, we control for this potential experience to the powers of 1 to 4, interacted with years of schooling. We also control for number of years since arrival to the U.S. for immigrants.

The regression controls for tenure and a large set of housing characteristics X_i^p, including number of rooms, and type and age of structure.[9] The fixed-effect coefficient $\hat{p}_j$ is the inferred housing cost differential, re-centered around the national average.

3.2. Immigration and Native Migration Data

Immigrants are defined here as foreign-born residents who are not U.S. citizens by birth. Natives are born in the U.S. or abroad to U.S. citizen parents. We split natives into migrants, who have left their birth state, and "stayers," who have not.

[PLACE TABLE 1 HERE]

Table 1 shows how the share of immigrants has grown from 13.4 percent to 17.1 percent of the population 25 years old or more. The share of native migrants has fallen from 35 to 33.3 percent. Immigrant shares are relatively small in some cities, especially when broken down by country of origin. To avoid sampling error from the the 5 percent sample, we use the Census Summary File 3 of 2000 (about 1 in 6 households) and 2012-2016 ACS 5-Year Data from National Historical Geographic Information System (Manson et al., 2017) to get the origin country breakdown. We are able to consistently identify 65 countries. Table A.1 provides the full breakdown, but as shown later in Table A.2, more than half of immigrants come from Latin America and the Caribbean. Europeans make up less than 13 percent, and are falling, while Asians make up 27 percent are growing.

Table 1 provides additional summary statistics for our immigrants, native migrants, and stayers groups. Relative to native migrants, immigrants are more likely to be male, married and have children, but are younger, less educated, and less likely to own their home.

[9] The full list of controls includes the number of rooms, type and age of the building, lot size, indicators for commercial use and condominium, and unit amenities (plumbing, kitchen in the unit).

3.3. Amenity Data

We collect data on natural and artificial amenities for U.S. metros and 65 identifiable origin countries. Natural amenities are geographic and climate time-invariant characteristics that inhabitants typically favor. The domestic list of amenities largely follows Albouy (2016), including minus heating degree days (warm winters), minus cooling degree days (cool summers),[10] sunshine (measured in percent from possible), proximity to coast, average slope, and latitude. For non-natural, or "artificial" domestic amenities, we use safety, measured as violent crime rates from FBI crime data.[11] We also consider supply restrictions in housing markets from the Wharton Residential Land Use Regulatory Index by Gyourko et al. (2008). To proxy for other artificial amenities, we use the overall size of the metro population, as well as the percentage of population with a tertiary education.[12] While neither population size nor composition are amenities, as such, they typically increase the variety and quality of amenities available in a city (Diamond, 2016).

Our data on natural amenities of immigrants' origin countries is more novel and taken from multiple sources. Heating and cooling degree days data are taken from the Climate Analysis Indicators Tool (CAIT) of the World Research Institute, reorganized by ChartsBin Statistics Collector Team (2011). Sunshine data are taken from multiple sources due to limited availability, and are not exactly comparable with the U.S. data we use.[13] Country-level slope measures are from the population weighted Terrain Ruggedness Index: hundreds of meters of elevation difference for grip points of 30 arc-seconds, calculated by Nunn and

[10] Degree days represent the days and energy needed to heat (heating degree days) or cool a home (cooling degree days) to human comfort level (65°F). For the subsequent analysis, we refer to minus heating degrees days as warm winters and minus cooling degree days as mild summers.

[11] Data downloaded from Office of Policy Development and Research (State of the Cities Data System): `https://socds.huduser.gov/FBI/FBI_Home.htm?`. For the 2000 samples, we use the violent crime rates in 1999. For the 2014 samples, we use the violent crime rates in 2009.

[12] A subsample of population 25 years or older is used to calculate the percentage. To be consistent with the country-level data, we follow ISCED 2011 and define tertiary education as an associate degree or more.

[13] Our main source of sunshine data is World Meteorological Organization (2010), accessible through UNdata, and the remaining missing data are obtained from World Weather and Climate Information (2016).

Puga (2012). The coastal proximity measure is percent of population near ice-free coast or rivers (Gallup et al., 1998). Unfortunately, we do not know where within a country immigrants come from, and must apply a single amenity value for each origin country.[14]

[PLACE TABLE 2 HERE]

Natural amenities of U.S. metros and immigrants' origin countries are summarized in Table 2 for 2000 and 2014. Immigrants to the U.S. on average come from countries that have milder winters and hotter summers than the United States, especially in 2014. We do not observe many other large changes over time.

Our data on artificial amenities of origin countries also comes from multiple sources. For crime, we use international homicide rates (number of deaths per 10,000 population) from United Nations Office on Drugs and Crime (2018) from 1990 to 2000 for the 2000 sample period, and from 2012 to 2016 for 2014. If homicide rates are entirely missing for any of the periods, we impute them using rates from the closest years.

The educational attainment measure we use is the percentage of the population with a completed tertiary (associate's or bachelor's) education, obtained from Barro and Lee (2013).[15]

Finally, we consider two distance variables. The first is proximity of an immigrant's origin country to the United States, measured by the distance between centroids. This may help capture migration costs. The second is the distance to the closest port of entry, which takes into account the fact that immigrants tend to settle near the place of arrival. We measure distances between the centroid of each metro and the closest port of entry: New

[14]There is substantial degree of heterogeneity in internal geography in some countries.Most of our origin country amenity measures are population-weighted. The amenity measures may be incorrect to the extent that immigrants come disproportionately from one area within a country.

[15]This is taken directly from The World Bank (2018). We use the percent of population 25 years old or older with a complete tertiary education. The authors follow ISCED classification scheme. There are 5 origin countries with missing educational attainment. For those countries, we use the predicted values from the regression of Barro-Lee measure on the percentage of U.S. immigrant population with at least an associate degree. The relationship is plotted in Figure A.5

York, San Francisco, Austin, Chicago, or Miami.

3.4. Transforming Immigrant Shares and Weighting

We use the log of the ratio of immigrant to natives, or log odds, as a measure of differential sorting. If N_j^I is the number of immigrants, and N_j^B is the number of natives in each metro j, the immigrant share is $s_j = N_j^I/(N_j^I + N_j^B)$. The log odds is $\ln\left[s_j/(1-s_j)\right] = \ln N_j^I - \ln N_j^B$. As it spans over the entire real line, the log odds has advantages as a dependent variable. We also use an analogous log odds of native migrants.

As immigrant shares can be imprecise in small metros, we weigh all regression analyses using the number of migrants, making them representative of migrants' individual experiences.

3.5. Social Networks and Immigrant Enclaves

To account for pre-existing social networks, we construct a measure of population, predicted by immigrant enclaves. Following Card (2001), this measure uses the total current number of immigrants, grouped by origin country, and distributes them across metros according to pre-existing shares:

$$Enclave_{jt} = \sum_{k=1}^{K} \frac{N_{jk,1980}}{N_{k,1980}} \times N_{kt} \tag{7}$$

where $N_{jk,1980}/N_{k,1980}$ is the share of immigrants from country k that resided in metro j in 1980, and N_{kt} is the national number of immigrants from that country at time $t = 2000$ or 2014.[16] We also construct a similar "native-migrant enclave" measure using states of birth

[16]This is a basic version of the labor-supply instrumental variable featured in Altonji and Card (1991), Card (2001) and other, designed to capture immigrants predicted by pre-existing immigration patterns, along with current migration. For more on this instrument, see Jaeger et al. (2018). To be consistent with the sorting measure in the paper, we take log odds of the enclave: $LogOdds_{jt}^{Enclave} = \ln[s_{jt}/(1-s_{jt})]$, where s_{jt} is the

rather than origin country.[17]

Besides just social networks, the enclave measure may capture residential amenities that immigrants gain from residing near those similar to them. Immigrants may want to be near others who share their native tongue, dance to similar music, or celebrate same holidays. They may also demand similar indivisible inputs, such as grocery stores or houses of worship. Or they may simply share similar tastes for amenities we do not observe.

4. WAGE, COST, AND LOCATION DIFFERENCES OF IMMIGRANTS AND NATIVES

[PLACE FIGURE 1 HERE]

Figures 1 through 3 document how wage, cost and location choices differ for immigrants and natives, using 2014 data.[18] Figure 1 shows that immigrants disproportionately sort toward big cities with high native populations. The log odds of immigrants and native population are highly correlated. At this point, it is difficult to state whether this is due to productivity or quality-of-life reasons.

[PLACE FIGURE 2 HERE]

Figure 2(a) graphs housing-cost differentials for immigrants and native migrants, plotting the within-metro difference between immigrants and native migrants against the across-metro differences for native migrants alone.

Immigrants on average pay 16 percent less in housing costs than native migrants. The negative slope of the fitted line suggests that the housing-cost gap between immigrants and native migrants tends to be larger in more expensive cities. Analogously in (c), we plot

ratio of immigrant enclave measure to total Metro population: $s_{jt} = Enclave_{jt}/N_{jt}$

[17]Historical patterns of within-U.S. migration have been used in literature to construct shift-share instruments, see, for example, Howard (2019).

[18]Table A.3 summarizes Figures 1 through 3.

the share of income spent on housing for immigrants and native migrants. We find that while immigrants pay less for housing on average, the income share spent on housing is 1 percentage point higher than native migrants. This number accounts for how immigrants live in more expensive cities.

We cannot determine from this data exactly why immigrants pay less for housing than natives. This phenomenon is the strongest in the most expensive cities, such as San Francisco and Honolulu. The most likely explanation is that immigrants live in less desirable — i.e., lower quality-of-life — neighborhoods within metro areas. An alternative explanation for why immigrants pay less is that their housing is of lower quality in terms of the dimensions we do not control for in the housing-cost index.[19]

In Figure 2(b), we examine the difference in the residualized wages between immigrants and native migrants. Even after controlling for observable characteristics, immigrants are paid 30 percent less than native migrants. Also, the negative fitted line indicates that the gap between immigrants and natives is the largest where the native pay is the highest. Thus, it appears that immigrants sacrifice more than native migrants in terms of wages to live in high-wage cities, and those cities tend to be large and expensive. Finally, (d) plots the difference in wage share of income for immigrants and natives against wage income share for natives. We observe that immigrant households rely more on wage income than native migrants by 10 percentage points. However, this gap becomes smaller in cities where the share of wage income is higher for native migrants.

[PLACE FIGURE 3 HERE]

While these differences are interesting, one should keep in mind that variation in within-

[19] Research shows that immigrants are more likely to occupy lower quality housing compared to natives. For example, Schill et al. (1998) show that the foreign-born have worse housing conditions, such as overcrowding and unsound building structures. Also, social networks may play a role in letting immigrants access lower-cost housing. For example, Moriah et al. (2004) shows that new Colombian immigrants in Toronto rely on social networks for housing access. An unlikely explanation is that immigrants pay less due to housing discrimination in their favor.

city differences between immigrants and natives are still rather small relative to the overall differences across cities. As a result, immigrants and natives show similar willingness to pay to be in the same metro areas, seen in Figure 3. While we examine further how these differences vary with amenities, the small differences underline the need to also consider sorting behavior.

5. ARE IMMIGRANTS PURSUING INCOME, AFFORDABILITY, OR AMENITIES?

5.1. Sorting by Prices and Wages

To see whether wages or amenities are more important in determining immigrant sorting behavior, we let the two compete in the following regressions:

$$\ln\left[s_{jt}/(1-s_{jt})\right] = \beta_p \hat{p}_{jt} + \beta_w \hat{w}_{jt} + \phi_t + \upsilon_{jt} \tag{8a}$$

$$= \beta_{WTP} W\hat{T}P_{jt} + \beta_A \hat{A}_{jt} + \phi_t + \upsilon_{jt} \tag{8b}$$

where the outcome variable is the log odds mentioned earlier.[20] The first regression uses the price and (nominal) wage differentials as the explanatory variables.

The explanatory variables in the second regression are "urban attributes," derived from these two differentials: willingness-to-pay, $W\hat{T}P_j$, and trade productivity, $\hat{A}_j$, as covered above.

[PLACE FIGURE 4 HERE]

[PLACE TABLE 3 HERE]

[20] In the empirical analysis, we pool the 2000 (Census) and 2014 (ACS 5-year 2012-2016) data, adding year indicators to the regression equations. This is mainly done for completeness and to improve power, especially for smaller metro areas.

The simple bivariate scatter plots in Figure 4 show that immigrants are positively correlated with both wages and housing costs. When both differentials are included in column 1 of Table 3 the coefficient on costs is positive and significant, but for wages it is negative, albeit marginally. This implies that immigrants sort more towards less affordable areas than high-wage areas.

These results are translated in column 4 into trade-productivity and willingness-to-pay. Immigrants sort strongly toward places where willingness-to-pay is high, but not trade productivity. This suggests immigrants may care more about favorable quality-of-life amenities than high wages[21]

We estimate the same regressions on the sample of native migrants in Table 3, Panel B. Panel C shows p-scores of tests on whether the coefficients of immigrants and native migrants are significantly different. Native migrants sort less strongly to high-cost areas. Rather, they sort toward places with lower nominal *and* real wages. Relative to immigrants, native migrants sort less toward high willingness-to-pay areas, and away from productive areas, possibly for cheaper housing.

In columns 2 and 5, we add enclave measures to the regressions. Enclaves strongly predict immigrant population: R-squared increases from 0.36 to 0.72 in both columns 2 and 5. However, the coefficients of housing cost and wages become insignificant. Indeed, the enclave measure, based on 1980 distribution of immigrants, is highly correlated with current immigrant shares. Adding enclaves to the regression is similar to taking a first difference. To the degree that wages and housing cost differences are persistent over time, these results indicate that immigrants' attraction to high-cost areas has not changed much over time.

[21]These results are also consistent with Albert and Monras (2018), who document that immigrants are concentrated in expensive cities which pay them high nominal wages. They argue that immigrants require lower compensation in nominal wages to live in expensive cities since they also consume goods and services in their home countries through remittances.

To understand what is responsible for this large change in the coefficients, column 3 regresses enclaves on wages and housing costs. The results indicate that immigrant enclaves are stronger in cities with lower nominal wages and higher housing costs. Column 6 finds that willingness-to-pay strongly predicts immigrant enclaves.

In sum, we find that the location of immigrant enclaves is not random; they are more likely to be in expensive cities where willingness-to-pay is high, similar to current immigrant settlement patterns. This raises an interesting question about the exogeneity condition need to use enclaves an instrument for labor supply. This assumes that the previous immigrant settlement patterns are not correlated with contemporaneous demand shifts or other, unaccounted for supply shifts. If the demand for amenities changes over time, the exogeneity restriction may be violated (Goldsmith-Pinkham et al., 2018, Borusyak et al., 2018).

The native-migrant enclave measure also predicts their sorting. Similar to immigrants, enclaves mute the relationship with urban attributes. Again, native enclaves are significantly correlated with contemporaneous urban attributes (columns 3 and 6). Conditional on their enclaves, native migrants still sort to cities with low nominal wages and low productivity. These results are significantly different from immigrants.

5.2. Addressing the Possible Role of Confounding Characteristics

Difference in sorting patterns between immigrants and native migrants could be due to either differences in observable (see Table 1) or unobservable individual characteristics correlated with immigrant status. To test if observable characteristics explain the different sorting patterns, we run two robustness checks.

First, we re-weigh immigrant observations to make the distribution of immigrant characteristics similar to those of native migrants.[22] Estimates for"reweighted" immigrants still

[22]We estimate revised weights by estimating a probit model on the sample of native and international migrants, using a native-migrant indicator as the outcome. Observable attributes, such as sex, age, race

show different sorting behavior than similar native migrants, as they move to cities with higher costs and willingness-to-pay (Table A.6).

Second, we rerun Table 3 using subgroups of immigrants: young (vs. old), single (vs. married), high educated (vs. low educated), recent migrants (vs. earlier migrants). Regardless of how we divide the samples, immigrants in general prefer cities with higher willingness-to-pay, though there are some differences between the subgroups (Table A.7).

5.3. Sorting over Prices and Wages by Country of Origin

To examine sorting patterns by region of origin, we split the sample of immigrants in nine groups: Canada, Latin America, Western and Northern Europe, Eastern and Southern Europe, Oceania, Eastern and Southern Asia, South Central Asia, Middle East and Northern Africa, and Sub Saharan Africa.[23] Table 4 summarizes the estimation results of Equation (8b) on those nine sub-samples.

[PLACE TABLE 4 HERE]

It appears that immigrants do trade off income and costs differently depending on where they come from. Immigrants from Latin America, the largest foreign-born population, sort toward high willingness-to-pay areas far more than immigrants from other regions. At the same time, Latin Americans are the only group that sorts toward places with lower trade-productivity. Immigrants from Western and Northern Europe are generally in place where willingness-to-pay is high, whereas those from Eastern and Southern Europe go after trade productivity. Immigrants born in East and Southeast Asia pursue both urban attributes. A good example is a high concentration of East Asian immigrants (from China and South Ko-

and education are used to predict this indicator. Then we multiply the census weights of immigrant by the odds predicted by probit model, run separately for 2000 and 2014. Probit regression results are reported in Table A.5. Odds for each immigrant observation i are $\frac{\hat{p_i}}{1-\hat{p_i}}$, where $\hat{p_i}$ is the predicted probability of being a native, conditional on migrating. We assign new weights for immigrants w_i that are equal to Census personal weight, multiplied by odds: $w_i = perwt_i \times \frac{\hat{p_i}}{1-\hat{p_i}}$. Since Census personal weights sum up to population, the re-weighted number of immigrants is the sum of our modified weights.

[23]For the detailed composition of the regions, see Table A.1.

rea) in California – one of the least affordable but most productive states. Immigrants from South Central Asia (including India and Pakistan) and Sub-Saharan Africa are generally found in cities with higher productivity.

5.4. Willingness-to-Pay and Sorting for Particular Amenities

Going back to seeing immigrants as a whole, our next step is to consider how immigrants value indivudal amenities differently. Following up on the discussion around equation (4), we regress immigrants' willingness-to-pay and log odds measures on individual amenities, and compare them to that of native migrants. Since these cross-sectional regressions are subject to omitted variables, simultaneity, and multicollinearity, one should not interpret the coefficients as causal.

[PLACE TABLE 5 HERE]

Table 5 shows the value of the natural and artificial amenities, estimated separately for immigrants in Panel A, and native migrants in Panel B. Panel C shows p-values of the difference between the coefficients for immigrants (Panel A) and native migrants (Panel B). Columns 1 to 2 and 3 to 4 illustrate how the individual amenities are correlated with willingness-to-pay and log odds. Columns 2 and 4 additionally include the enclave measures in the regressions (immigrant enclaves in Panel A and native migrant enclaves in Panel B). Overall, there is little difference between the coefficients with and without the enclave controls, except for educational attainment.

The estimates in the first rows of Panels A and B show that immigrants pay more to be in highly populated metros, whereas native migrants show no strong pattern (see also Figure 1). The contrast is even greater sorting: immigrants locate more in larger metros, while the opposite is true for native migrants. These patterns do not change after controlling for enclave effects. The complementary results imply that the labor supply of immigrants to larger metros is generally greater than for smaller ones for reasons beyond that of just pre-existing immigrant networks.

Moving to natural amenities in the next five rows, there is some evidence that immigrants and natives value these amenities differently (columns 1 and 2). Willingness-to-pay of both immigrants and native migrants are rather similar and positively associated with mild summers, sunshine, proximity to coast and average slope. Immigrants, however, value proximity to coast slightly more than natives, who in turn seem to value warm winters more. Controlling for enclaves does weaken the significance of some of these effects, but does not undo them.

Immigrants and native migrants also exhibit differences in sorting patterns for natural amenities (columns 3 and 4). Native migrants sort into places with warmer winters and hotter summers. They also move away from coasts when we condition on enclaves. In contrast, the foreign-born sort to sunnier and hillier areas. Without the enclave control, immigrants seem to be less sensitive to temperature than native migrants. Conditioning on enclaves, however, they sort toward places with warmer winters and hotter summers, and away from coasts, much like native migrants.

As expected, proximity to ports of entry predicts a larger proportion of immigrants. It also predicts fewer native migrants. It is not significantly associated with greater willingness-to-pay for either group.

Moving to artificial amenities, a few more patterns arise. First, both immigrants and native migrants seem to pay more to be in safe cities with less violent crimes, although the effect is more precise for natives. Oddly, native migrants tend to move away from safer cities, although this result loses significance when controlling for enclave effects.

There is a contrast in how natives and immigrants value metros where educational attainment is high. In terms of of willingness-to-pay, both groups appear to sacrifice 3 percent of their income for a 10-percentage point increase in the share of college-educated adults.

In contrast, natives sort more into educated cities, while immigrants exhibit the opposite pattern, at least without the enclave control. This negative sorting relationship for immigrants appears by their attraction to Hispanic enclaves where education is low (see Table A.12).[24] Once enclaves are included in column 4, the coefficient for immigrant flips sign, becoming positive, albeit smaller in magnitude than for native migrants.

Compared to native migrants, immigrants sort into more places with greater land-use regulation. Those places tend to have high inefficiently high housing costs (see Saiz (2007), Albouy and Ehrlich (2017)).

Finally, the estimates shed light on the value of enclaves themselves, conditioning on the amenities and other controls. First, immigrants are willing to pay more to be in cities with deeper enclaves. This complements the more standard finding that they sort into places with enclaves. Overall, this implies that enclaves are a source of quality of life for immigrants, that shift out their labor supply curve. The results for native migrants do not show them paying more to be in places with people of similar birth states. The sorting behavior is consistent. Overall it is less clear if native enclave effects are driven by shift in the supply curve driven by quality-of-life effects, or something else, such as from better information about job opportunities in an area.[25]

[24]Among the nine country groups, Latin America is the only region that has a statistically significant negative coefficient of educational attainment.

[25]Table A.9 explores heterogeneity in amenity valuation of immigrants by their date of arrival to the U.S. Overall, the value of amenities are very similar for recent and early migrants. One noticeable exception is sorting of recent migrants toward more educated cities.

6. AMENITIES LOST, FOUND, AND RECOVERED

6.1. Predicting Migration with Amenities in Origin Countries

While the previous section analyzed the "pull" factors that draw in immigrants, this section analyzes the "push" factors that compel immigrants to move from their origin countries. While previous researchers have examined the role of income and distance (Karemera et al., 2000, Mayda, 2010, Clark et al., 2007), none have examined the role of level differences in amenities, such as climate.[26] Yet, given how important climate is in determining migration *within* the U.S. (Rappaport, 2007), it may play a large role in determining migration *to* the U.S. Other amenity factors related to lack of safety or low levels of education in the community may also play a roll in pushing out emigrants.

The standard push model predicts immigration to the U.S based on origin country income, distance, and total population. We augment this model to include origin country amenities:

$$\ln(N^I_{kt}) = \beta_0 \text{Pop}_{kt} + \beta_1 \text{GDP}_{kt} + \beta_2 \text{GDP}^2_{kt} + \beta_3 \text{Dist}_k + \sum_a \pi_a Z_{kat} + \tau_t + \epsilon_{kt} \tag{9}$$

where $\ln(N^I_{kt})$ is the logarithm of the total number of immigrants to the U.S. from country k at time t. Pop_{kt} is the logarithm of origin country population and Dist_k is the logarithm of the distance, taken from the population centroid. As is standard, the model includes a quadratic in income, log GDP per capita, GDP_{kt} (Hatton and Williamson, 2005). As described earlier, the amenity measures for countries of origin are more limited than for metro areas, and include the five natural amenity variables, and two artificial amenity measures, safety (measured in homicide rate) and human capital (measured in educational attain-

[26] As mentioned before, the role of climate *change* has been examined, but surprisingly not climate levels.

ment).

[PLACE TABLE 6 HERE]

Table 6 shows the estimates from equation (9). Columns 1 and 2 include either only standard push variables or amenity variables, separately. Column 3 includes them together. Columns 1 to 3 show results at the country level, while in column 4, the outcome is the number of immigrants from country k in metro j, which is the outcome in the next table. It uses distance to individual metro areas from each country, as opposed to the center of the United States.

The results for the standard push variables change little across specifications. Not surprisingly, more immigrants come from large countries, albeit at a less than proportional rate: a 10 percent increase in population leads to a 5 to 6 percent increase in the number of immigrants. Income has a non-linear effect with an inverse U-shape, reflecting how immigrants from low-income countries may not have the capital, networks, information, or right to move. Higher income thus raises migration. Beyond per-capita incomes of 3 to 4 thousand dollars, the relationship reverses, as income gains from moving become smaller. Finally, distance tends to deter migration because of higher migration costs. The effect is fairly high: a 10 percent increase in distance reduces immigration by 16 percent. Indeed, this helps to explain higher immigration levels from Latin America.

Using only seven amenities, the results in column 2 show that countries with warmer winters and educated populations are greater sources of immigrants. Without controlling for distance to the U.S. and other standard push factors, coastal proximity appears to have a negative effect, which is odd. Naturally, this amenity-only regression is subject to omitted variable bias, particularly given its low explanatory power compared to column 1 (an adjusted R^2 of 0.33 compared to 0.83).

The augmented push model column 3 changes strengthens the results on the standard push variables, while changing the results on amenities. Only a few amenities are significant at the 10 percent level. First, immigrants tend to leave countries that lack sunshine.

Second, countries that are safer send more immigrants, conditional on income and other factors. This is rather surprising since one would normally expect immigrants to want to flee more dangerous countries.[27]

Third, once standard push factors are included, coastal countries provide more immigrants. Indeed, such countries traditionally have greater trade and more connected to the rest of the world.

Notably, the result for warm winters becomes insignificant, while the result for mild summers becomes slightly negative. Indeed, the two variables are rather collinear, making it hard to distinguish the impact. Overall, however, the evidence does not seem to support the idea that extreme heat drives immigration to the U.S.

Finally, we find positive but insignificant coefficients for educational attainment. Thus, conditional on income and other variables, educational attainment is not a particularly important predictor of immigration.[28]

6.2. Amenities Recovered

This section attempts to synthesize both the pull and push factors of immigration by considering considers how amenities in an immigrants' origin country is related to the current city they live in. As mentioned earlier, immigrants may decide to live in cities that have similar amenities to their origin simply from habit or to minimize adaptation costs. Alternatively, immigrants may purposefully self-select to the U.S. to seek out completely different amenities than what is available where in their origin.

[27] We have also analyzed the impact of organized violence (state-based, non-state based conflicts and one-side violence). This measure is not statistically significant.

[28] According to the human capital theory of immigration, countries with higher education tend to be a source of more immigrants since more educated immigrants are likely to have lower risks of migration through a higher ability to collect and process information. See Massey et al. (1993) for a review of international migration theories. These are instances of "human capital flight": immigrants from these regions generally have much higher educational attainment than average in their home countries.

To formally analyze this relationship, the estimated regression interacts the amenities in the U.S. cities with those of origin countries:

$$LogOdds_{jkt} = \sum_a \gamma_a (Z_{ja} \times Z_{ka}) + \phi_j + \phi_k + \phi_t + \epsilon_{jkt} \tag{10}$$

where Z_{jk} and Z_{ja} are amenities from origin country k and the U.S. city j; ϕ_t is a time indicator. Because it examines city-country matches, this regression can control for country fixed effects, ϕ_k, as well as city fixed effects, ϕ_j.[29]

[PLACE TABLE 7 HERE]

Table 7 reports the estimated γ_a – the coefficients of the interaction between the U.S. cities' amenities and origin countries' amenities. Column 1 includes metro area fixed effects and the standard push variables. Columns 2 and 3 control for country fixed effects, which absorb all potential push factors, forcing the relationships to rely completely on the interactions. Finally, we exclude immigrants from Latin American countries in column 4.[30]

Overall, most of the results are similar across specifications and support the idea that immigrants value amenities similar to those of their origin countries along some dimensions. In terms of natural amenities, immigrants from countries with more hills and warm winters seek the same in the cities they migrate to. The coefficients of proximity to coast and sunshine are also positive, even though they are not statistically significant.

There is also a similar pattern for safety: immigrants from countries with low homicide rates tend to live in U.S. cities with relatively low violent crime rates.[31] In other words,

[29]Because of the multiple dimensions (city, country and time) of the outcomes, there are multiple possible weights. Here, we use a predicted number of immigrants in city i from origin country k in year t, $\hat{s_{jt}} = N_{jt} \times s_{kt}$. That is, we multiply the national share of immigrants from country k by the total population in city j. This puts more weights on countries with more immigrants and on larger cities.

[30]The full list of estimated coefficients is in Table A.15.

[31]For the U.S. cities, we use violent crime rates instead of homicide rates, which is the number of violent crimes per 1,000 population. We perform the similar analysis in Table A.16, interacting international homicide rates with homicide rates per 10,000 population in the U.S. cities. The coefficients are similar, but the standard errors are larger, probably because of greater noise in homicide rates.

immigrants from less safe countries tend to live in less safe U.S. cities. It is possible that immigrants' perception on safety can depend on their exposures to violence in origin countries. That is, immigrants born in unsafe countries may be less sensitive to high violence (perceive it as normal), while immigrants born in relatively safer places have higher fear of crime because of lower exposure.[32]

The main exception to the pattern of immigrants seeking similar amenities pertains to educational attainment, although this is not a true "amenity" as discussed earlier. Instead, coefficients for the interaction term of percent tertiary education are negative: immigrants from countries with a smaller share of adults with tertiary schooling tend to sort to the U.S. cities with a more educated population. On the other hand, highly-educated immigrants settle in more educated cities: when we interact educational attainments of the U.S. cities and schooling of immigrants in the United States, the coefficient is positive (see Table 7, column 3).

These contrasting results can be explained by stayers (current residents) and movers (immigrants) from origin countries having different levels of human capital.[33] As suggested by a "human capital flight" story, highly educated individuals in developing countries, with generally lower level of education, have more incentives to emigrate. Once they enter the United States, they choose to live in cities with more educated workers. Moreover, migration costs for less-educated workers from distant countries may be too high. These seemingly contradictory results stem from immigrants differing considerably from

[32]Using the data from Gallup 2018 Global Law and Order Index (Gallup Inc., 2018), Quartz plotted perception of crime (percent of residents feeling unsafe walking alone at night) versus actual crime rates (percent people experienced violence or theft in the past year). The results reveal that people in relatively safe countries (Moldova, Cambodia, etc.) feel more unsafe than the linear trend would predict, and people from high-crime countries (Ghana, Sudan, Sierra Leone) feel much more safe than predicted by trend (`https://qz.com/1308707/what-makes-a-country-dangerous/`). In our context, people from unsafe places can go to high-crime cities simply because they are not afraid of them.

[33]In Figure A.5, we plot the human capital level of origin countries on the human capital level of immigrants in the United States. Many countries (India, for example) have significant differences in educational attainment between the average population that reside in these countries and the U.S. immigrant population.

residents in the home country.

7. CONCLUSION

Given that economists generally model immigrants as pursuing greater market consumption, it is seems surprising that they live in places that are so expensive. Yet, theories of spatial equilibrium imply that the lower real wages immigrants receive from picking such expensive cities is compensated for by quality-of-life amenities.

In particular, immigrants seem to gravitate towards natural amenities such as sunshine and hilly geography. Most of all, immigrants seem to care for large, often coastal cities, known for their diversity. Native migrants, on the other hand, move to smaller cities, albeit ones that are relatively expensive and highly educated. This supports an interesting, if ancient, pattern whereby migrants land initially on coasts, but over time, eventually move inland. Natives do seem to be choosy in where they move, as they too move to higher-amenity areas.

Our results highlight that the pursuit for amenities may play as much of a role in determining where immigrants locate as jobs. In other words, factors that affect labor supply may be as important as those that affect labor demand. This may explain the fact that many immigrants already see enormous income gains by moving to the U.S., and care not only for market goods, but for non-market goods as well. As our push regressions suggest, some may indeed pursue better amenities than in their origin country. Nevertheless, immigrants also seek out amenities, as well as people, that resemble those of their origin countries. Indeed, the amenities that remind someone of home may be the kind of amenities most worth paying for.

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FIGURE 1: Immigrants Sort Toward Large Metropolitan Areas (2014)

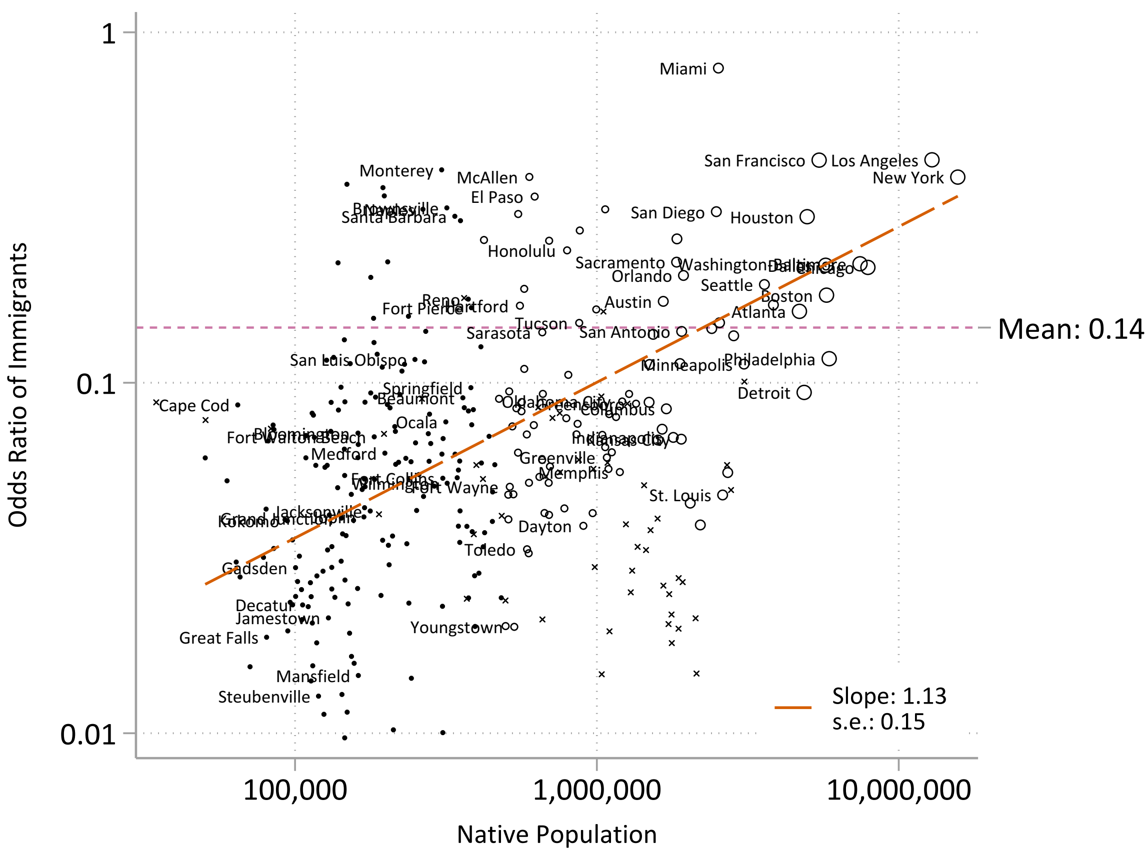
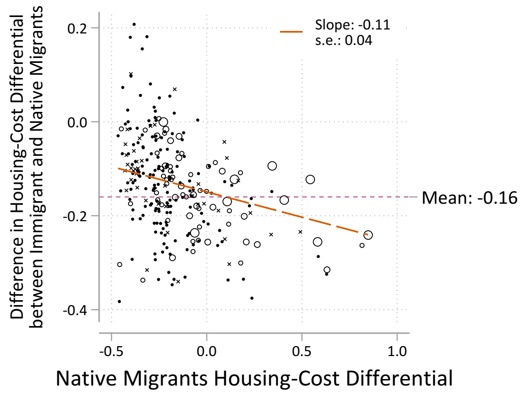
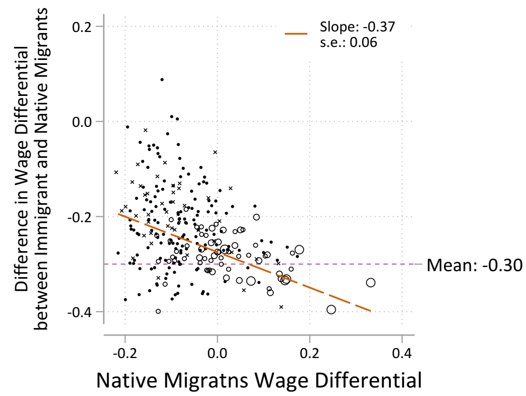


FIGURE 2: Difference in Housing Costs and Wages between Immigrants and Native Migrants

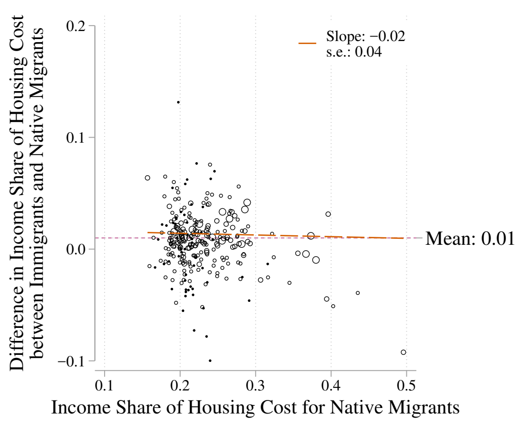
(a) Housing-Cost Differentials



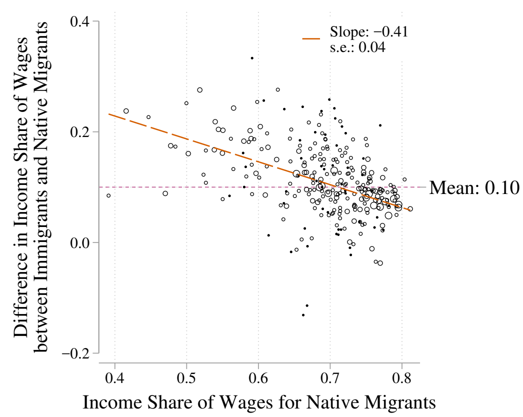
(b) Wage Differentials



(c) Income Share of Housing Costs



(d) Income Share of Wages



Note: Observations are weighted by total metro population. (a) plots native migrant housing-cost differential $\hat{p}_j^{NM}$ on the X-axis and the difference between immigrant and native migrant housing-cost differentials on the Y-axis: $\hat{p}_j^{I} - \hat{p}_j^{NM}$. (b) plots native migrant wage differential $\hat{w}_j^{NM}$ on the X-axis and the difference between immigrant and native migrant wage differentials on the Y-axis: $\hat{w}_j^{I} - \hat{w}_j^{NM}$. Income share of wages in (c) is calculated as a fraction of wages of all household members in total household income.

FIGURE 3: Willingness-to-Pay of Native Migrants and Immigrants

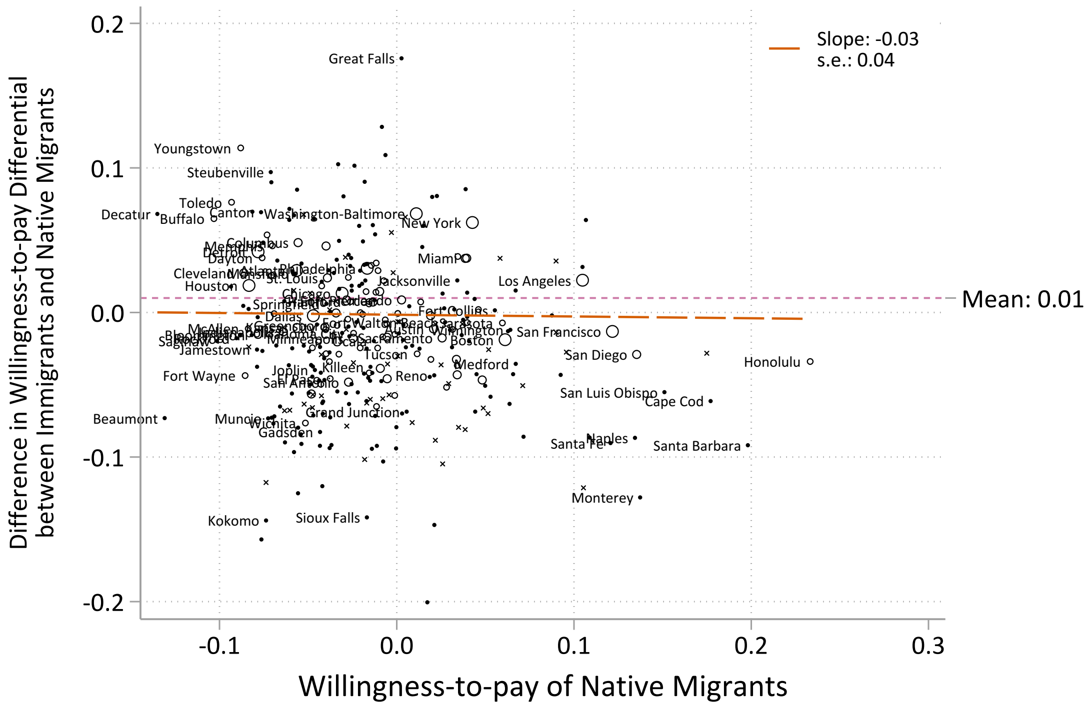


FIGURE 4: Immigrants Live Disproportionately in High-Wage and High-Cost Areas

(a) Wage Differentials

(b) Housing-Cost Differentials

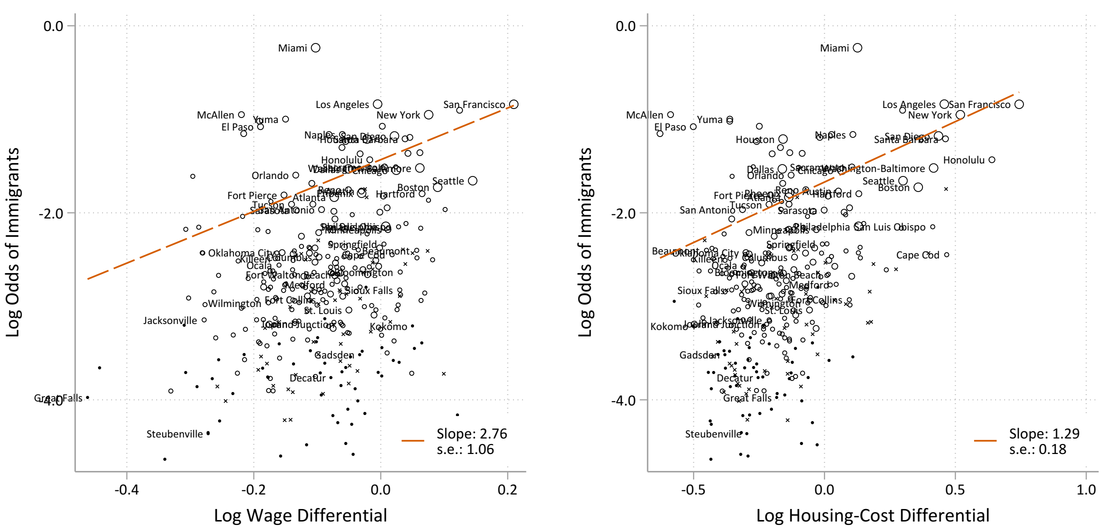


TABLE 1: Characteristics of Immigrants, Native Migrants and Natives in Birth States (25 years or older)

	Immigrants		Native Migrants		Natives in Birth State	
	2000	2014	2000	2014	2000	2014
Share of Population	13.4	17.1	35.0	33.3	51.7	49.6
Male	48.7	48.2	47.8	48.3	47.5	48.2
Married	68.1	64.2	63.6	57.9	61.5	53.3
Avg. Age	45.5	48.4	50.2	52.9	48.7	50.2
Avg. Number of Children	1.20	1.09	0.75	0.65	0.82	0.70
Homeowner	55.2	55.4	73.6	70.1	76.9	72.6
Graduate Degree	10.3	12.2	11.9	15.2	6.5	8.7
College Degree	13.7	16.8	19.2	22.4	13.5	17.0
Some College	14.5	15.7	22.5	24.3	20.4	24.5
High School Degree	19.2	20.0	24.9	19.6	33.6	27.6
Less Than High School	38.2	29.7	14.1	8.0	18.6	10.7

Notes: Summary statistics are for age 25+. Summary statistics for all population are in Table A.4. Graduate degree is defined as master's, professional (beyond bachelor's) or doctoral degree. College degree is defined as bachelor's degree. Some college is defined as associate's degree or one or more years of college without a degree. High school is defined as high school diploma or GED. Rows 1-3 and 6-11 are in percent. The number of children in the household is the number of own children of all ages living with respondents.

TABLE 2: Average Amenities in the U.S. and Immigrant Countries of Origin

	U.S.		Immigrant Origin Countries		
	2000	2014	2000	2014	Change
	(1)	(2)	(3)	(4)	(5)
Cold Winter	4.30	4.30	1.92	1.69	-0.23
Hot Summer	1.32	1.32	1.67	1.77	0.11
Sunshine	0.32	0.32	0.27	0.27	0.00
Close to Coast	0.65	0.65	0.47	0.46	-0.01
Average Slope	0.33	0.33	0.66	0.66	0.00
Homicide Rate	6.55	4.63	9.85	11.31	1.46
Percent Tertiary Degree	26.73	30.94	8.76	11.29	2.53

Notes: Table shows average amenities of the U.S. (column 1) and immigrant origin countries by year (columns 2-3). Columns 2 and 3 are weighted by immigrant origin country population. The national-level measures of U.S. amenities in column 1 are different from the metro-level data in the main analysis, but shown for illustrative purpose. Cold winter (hot summer) is measured with heating (cooling) degree days that estimates the amount of energy to heat (cool) a building to the human comfort temperature (65°F). Sunshine measure is the (average sunshine time)/(total time). Close to coast measure is the share of population near ice-free coast or river (Gallup et al., 1998). Average slope is the population weighted Terrain Ruggedness Index (Nunn and Puga, 2012). Homicide rate is the number of homicides per 100,000 population. Percent tertiary degree is percent of population 25+ years old with completed tertiary education (Barro and Lee, 2013). Because of the data limitations, we use 2010 educational attainment data for year 2014. Summary statistics by region is in Table A.2.

TABLE 3: Immigrant and Native Migrant Sorting by Prices, Wages and Urban Attributes (2000 and 2014)

	Log Odds		Enclave	Log Odds		Enclaves
	Enclaves excluded	Enclaves included		Enclaves excluded	Enclaves included	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Immigrants					
Wage	-2.64	0.02	-5.07**			
	(1.62)	(1.01)	(2.06)			
Housing Cost	1.99***	0.11	3.59***			
	(0.42)	(0.27)	(0.70)			
Immigrants Predicted by 1980 Enclaves		0.53***			0.52***	
		(0.05)			(0.05)	
Trade-Productivity				0.71	0.18	1.02
				(1.08)	(0.75)	(1.22)
Willingness-to-Pay				5.87***	0.39	10.52***
				(1.58)	(0.99)	(2.39)
R^2	0.36	0.72	0.45	0.36	0.72	0.45
	Panel B: Native Migrants (Cross State)					
Wage	-2.77***	-1.65**	-1.58**			
	(0.86)	(0.68)	(0.66)			
Housing Cost	0.69*	0.02	0.96***			
	(0.36)	(0.38)	(0.20)			
Native Migrants Predicted by 1980 Enclaves		0.71***			0.70***	
		(0.10)			(0.10)	
Trade-Productivity				-1.91***	-1.76***	-0.22
				(0.61)	(0.34)	(0.48)
Willingness-to-Pay				2.96**	0.81	3.06***
				(1.18)	(1.19)	(0.73)
R^2	0.13	0.42	0.11	0.14	0.43	0.11
	Panel C: Difference between Immigrants and Native Migrants (p-score)					
Wage	0.93	0.06	0.03			
Housing Cost	0.01	0.82	0.00			
Enclaves		0.08			0.09	
Trade-Productivity				0.02	0.00	0.29
Willingness-to-Pay				0.08	0.73	0.00

Notes: Robust standard errors are clustered at metro level and shown in parentheses. In columns 1, 2, 4 and 5, dependent variables are log odds immigrants for Panel A and log odds native migrants for Panel B. In columns 3 and 6, dependent variables are immigrants enclaves for Panel A and native migrant enclaves in Panel B. We add year indicators in all columns. Regressions are weighted by metro immigrant population in Panel A and metro native population in Panel B. Urban attributes are calculated using the methodology from Albouy (2016), restricting samples to immigrant population in Panel A and native migrant population in Panel B. In Panel C, we report p-scores for testing the difference in the coefficients between Panels A and B. ***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE 4: Country of Origin Differences in Immigrant Sorting (measured by log odds) by Urban Attributes

	Latin America (1)	East/Southeast Asia (2)	South Central Asia (3)	East/South Europe (4)	West/North Europe (5)	Middle East (6)	Sub Saharan Africa (7)	Canada (8)	Oceania (9)
Trade-Productivity	-3.15*	3.88***	4.38***	5.58***	1.57***	2.01*	4.12***	0.48	2.73*
	(1.68)	(0.71)	(0.48)	(1.63)	(0.32)	(1.04)	(1.37)	(0.73)	(1.58)
Willingness-to-Pay	6.96***	5.97***	1.32	-0.06	3.46***	3.58	-1.88	1.27	5.17
	(2.26)	(1.53)	(0.89)	(2.37)	(0.72)	(2.33)	(2.14)	(1.08)	(4.27)
R^2	0.20	0.68	0.62	0.39	0.52	0.29	0.27	0.04	0.24
Share of Immigrants	0.511	0.192	0.074	0.069	0.052	0.031	0.030	0.021	0.005

Notes: Robust standard errors (in parentheses) are clustered by metro area. We include year indicators in all columns. Regressions are weighted by total immigrant population from each origin country. Detailed composition of regions is in Table A.1. Urban attributes are calculated using foreign born population only. The share of immigrants for each region is calculated using the average population of 2000 and 2014 in metropolitan areas.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE 5: Immigrant and Native Migrant Sorting and the Value of Individual Amenities

	Willingness-to-Pay		Log Odds	
	Enclaves excluded	Enclaves included	Enclaves excluded	Enclaves included
	(1)	(2)	(3)	(4)
Panel A: Immigrants				
Logarithm of Metro Population	0.018***	0.011**	0.284***	0.111***
	(0.004)	(0.004)	(0.024)	(0.033)
Warm Winters	-0.007	-0.004	0.032	0.090***
[base 65, minus heating degree days]	(0.006)	(0.005)	(0.059)	(0.034)
Mild Summer	0.028***	0.021**	-0.118	-0.276***
[base 65, minus cooling degree days]	(0.010)	(0.009)	(0.123)	(0.079)
Sunshine	0.156*	0.089	2.019**	0.421
[out of percent possible]	(0.089)	(0.078)	(0.943)	(0.634)
Close to Coast	0.005***	0.004***	0.010	-0.012*
[miles, minus square root of distance]	(0.001)	(0.001)	(0.008)	(0.007)
Average Slope of Land	0.006**	0.004*	0.129***	0.066***
[percent]	(0.002)	(0.002)	(0.029)	(0.018)
Close to Ports of Entry	-0.000	-0.001	0.030***	0.015***
[miles, minus square root of distance]	(0.001)	(0.001)	(0.005)	(0.004)
Safety	0.045	0.030	0.075	-0.298
[minus number of violent crimes per 1,000]	(0.037)	(0.034)	(0.314)	(0.193)
Percent Tertiary Degree	0.302***	0.412***	-1.249*	1.422**
	(0.071)	(0.075)	(0.740)	(0.558)
Wharton Land Use Regulatory Index	0.002	-0.002	0.170***	0.081*
	(0.005)	(0.005)	(0.057)	(0.048)
Immigrants Predicted by 1980 Enclaves		0.017***		0.411***
[log odds]		(0.006)		(0.049)
R^2	0.73	0.75	0.80	0.89
Panel B: Native Migrants (Cross State)				
Logarithm of Metro Population	-0.004	-0.004	-0.122***	-0.094***
	(0.003)	(0.003)	(0.034)	(0.030)
Warm Winters	0.015***	0.014***	0.101**	0.056*
[base 65, minus heating degree days]	(0.004)	(0.004)	(0.047)	(0.033)
Mild Summer	0.033***	0.034***	-0.455***	-0.396***
[base 65, minus cooling degree days]	(0.006)	(0.005)	(0.101)	(0.104)
Sunshine	0.211***	0.198***	-0.009	-0.845
[out of percent possible]	(0.047)	(0.045)	(0.665)	(0.610)
Close to Coast	0.002***	0.002***	-0.008	-0.018***
[miles, minus square root of distance]	(0.001)	(0.001)	(0.008)	(0.006)
Average Slope of Land	0.006***	0.006***	0.020	-0.004
[percent]	(0.002)	(0.002)	(0.025)	(0.023)
Close to Ports of Entry	0.000	0.000	-0.028***	-0.020***
[miles, minus square root of distance]	(0.001)	(0.001)	(0.006)	(0.005)
Safety	0.039**	0.044**	-0.362**	-0.040
[minus number of violent crimes per 1,000]	(0.017)	(0.017)	(0.170)	(0.159)
Percent Tertiary Degree	0.315***	0.300***	4.504***	3.485***
	(0.046)	(0.048)	(0.723)	(0.512)
Wharton Land Use Regulatory Index	0.006*	0.006*	0.008	0.011
	(0.003)	(0.003)	(0.043)	(0.038)
Native Migrants Predicted by 1980 Enclaves		0.009		0.586***
[log odds]		(0.006)		(0.068)
R^2	0.70	0.70	0.53	0.70
Panel C: Difference between Immigrants and Native Migrants (p-score)				
Logarithm of Metro Population	0.00	0.00	0.00	0.00
Warm Winters	0.00	0.00	0.37	0.49
Mild Summer	0.43	0.11	0.02	0.31
Sunshine	0.39	0.11	0.10	0.12
Close to Coast	0.00	0.04	0.23	0.63
Average Slope of Land	0.99	0.51	0.04	0.04
Close to Ports of Entry	0.21	0.02	0.00	0.00
Safety	0.83	0.68	0.38	0.43
Percent Tertiary Degree	0.84	0.21	0.00	0.05
Wharton Land Use Regulatory Index	0.56	0.27	0.11	0.39
Enclaves		0.31		0.03

Notes: Robust standard errors are clustered by metro and shown in parentheses. We control for the latitude and include year indicators in all columns. The dependent variables in columns 1 and 2 are willingness-to-pay of immigrants (Panel A) and native migrants (Panel B). The dependent variables in columns 3 and 4 are log odds of immigrants (Panel A) and native migrants (Panel B). Columns 2 and 4 additionally include immigrant enclaves (native migrant enclaves in Panel B). Regressions are weighted by metro immigrant (native) population in Panel A (Panel B). Panel C reports p-scores for testing the difference between the coefficients in Panel A and Panel B.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE 6: Immigration Push Factors by Country of Origin

Dependent Variable: Log of Immigrant Population	Country Level			Metro Level
	Only Standard	Only Amenities	Standard & Amenities	Standard & Amenities
	(1)	(2)	(3)	(4)
Logarithm of Origin Country Population	0.55***		0.62***	0.53***
	(0.03)		(0.07)	(0.05)
Logarithm of Per Capita GDP	1.52		1.83**	1.70**
	(0.97)		(0.87)	(0.85)
Logarithm of Per Capita GDP, Squared	-0.10*		-0.11**	-0.10**
	(0.06)		(0.05)	(0.05)
Logarithm of Distance to USA	-1.48***		-1.55***	-1.55***
	(0.16)		(0.14)	(0.11)
Warm Winters		0.53**	0.04	0.02
[Minus Heating Degree Days]		(0.23)	(0.07)	(0.05)
Mild Summers		0.26	-0.27	-0.28*
[Minus Cooling Degree Days]		(0.38)	(0.18)	(0.14)
Close to Coast		-1.70**	0.63*	0.41
[Percent Pop 100km from Coast]		(0.65)	(0.37)	(0.30)
Average Slope		0.37	0.47	0.47
[Population Weighted TRI]		(0.64)	(0.32)	(0.31)
Sunshine		-2.31	-3.59*	-3.62**
[Percentage of Available Sunshine Time]		(4.29)	(1.94)	(1.71)
Safety		0.03	0.16**	0.14**
[Minus Number of Homicides Per 10,000]		(0.17)	(0.07)	(0.07)
Education Attainment		7.23*	2.19	1.46
[Percentage of Tertiary Schooling]		(3.99)	(1.40)	(1.52)
Adjusted R^2	0.83	0.33	0.88	0.87
Number of Observations	130	130	130	29073
Number of Countries	65	65	65	
Metro Fixed Effects				Y

Notes: Robust standard errors are clustered by origin country in columns 1 to 3, and by metro and origin country in column 4. We include year indicators in all columns. In columns 1 to 3, the outcome varies at the country of immigrant origin level only. In column 4, the outcome varies at country of immigrant origin and metro area levels. Regressions are weighted by total immigrant population from each country in columns 1 to 3 and immigrant population from each country in each metro in column 4. Column 4 uses distances to metros instead of distances to the centroid of the U.S. There are 276 metros in column 4.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

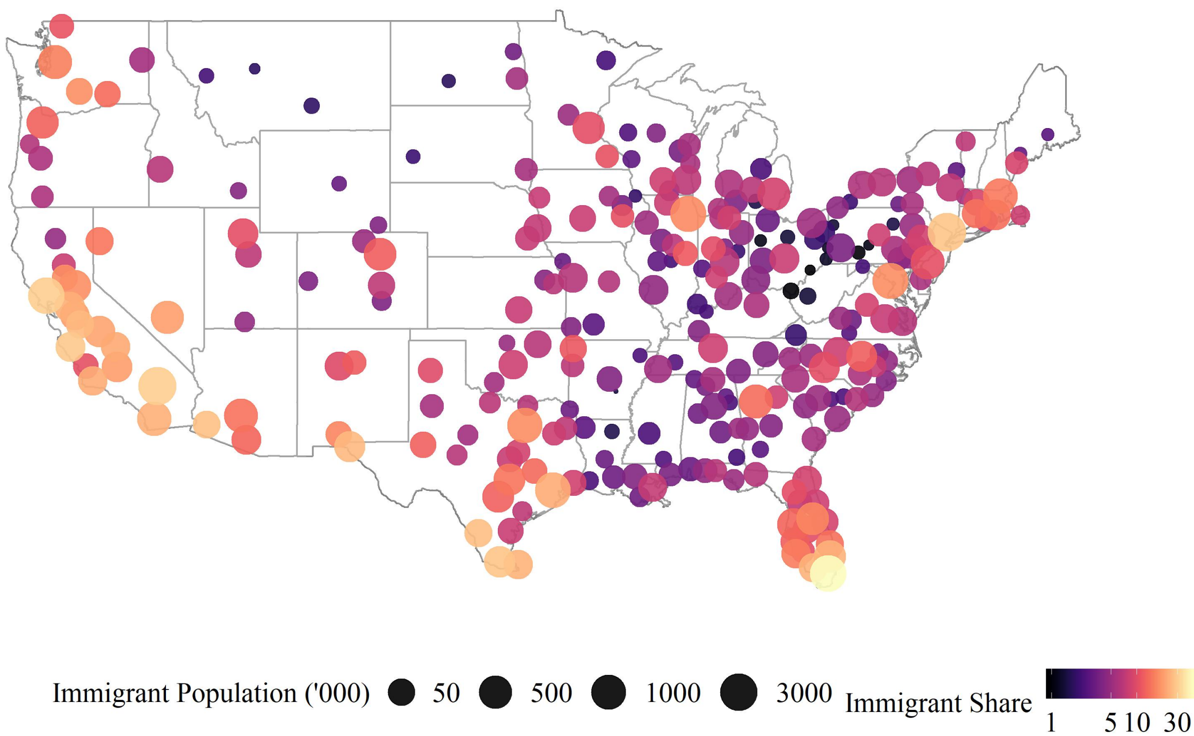
TABLE 7: Immigrant Locations, and Interaction between Destination City and Origin Country Amenities: A "Push-Pull" Model of Migration

Dependent Variable: Log Odds of Immigrant	(1)	(2)	(3)	(4)
Warm Winters	0.04**	0.04**	0.04**	0.02**
[Home Country × Destination City]	(0.02)	(0.02)	(0.02)	(0.01)
Mild Summer	-0.04	-0.05	-0.04	-0.03
[Home Country × Destination City]	(0.08)	(0.09)	(0.08)	(0.03)
Close to Coast	2.62	2.25	2.44	1.40
[Home Country × Destination City]	(9.90)	(10.93)	(10.78)	(9.12)
Average Slope	0.32**	0.32**	0.33**	0.04
[Home Country × Destination City]	(0.15)	(0.15)	(0.15)	(0.07)
Sunshine	0.14	0.14	0.15	0.12*
[Home Country × Destination City]	(0.13)	(0.13)	(0.14)	(0.07)
Safety	0.21**	0.17	0.18	0.16***
[Home Country × Destination City]	(0.09)	(0.11)	(0.12)	(0.05)
Percent Tertiary Education	-16.24*	-7.04**	-9.30***	-9.04***
[Home Country × Destination City]	(8.88)	(2.84)	(2.30)	(2.76)
Percent Tertiary Education			6.03***	4.40***
[Immigrants from Same Country × Destination City]			(1.21)	(1.18)
R^2	0.67	0.76	0.76	0.77
Number of Observations	28830	28830	28830	22105
Number of Countries	65	65	65	50
Metro Fixed Effects	Y	Y	Y	Y
Country Amenities Controls	Y			
Country Fixed Effects		Y	Y	Y
Excludes Latin American Immigrants				Y

Notes: The covariates are the interaction terms between the amenities of origin countries and amenities of U.S. metros. Robust standard errors (in parentheses) are clustered by metro and origin country. Regressions are weighted by the predicted number of immigrants from each origin country in each metro area (refer to Section 6.2 for the construction of weights). Year indicators are included in all columns. Column 1 controls for country level amenities, columns 2 to 4 control for country fixed effects instead. Column 4 excludes immigrants from Latin American countries.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

Appendix - For Online Publication

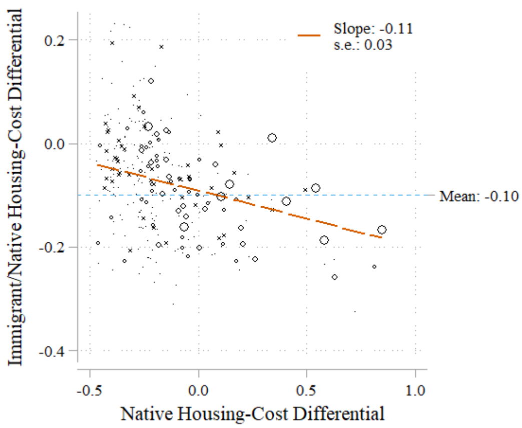
FIGURE A.1: Distribution of Immigrants across Metro Areas in 2014



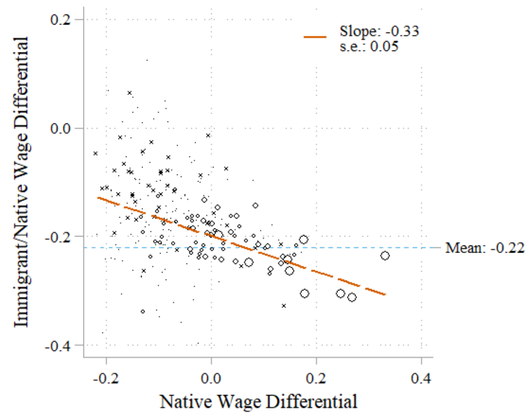
Notes: Color reflects immigrant shares — the percentage of immigrant population in the metro areas. Size of the bubbles reflects the size of immigrant population in thousands.

FIGURE A.2: Difference in Housing Costs and Wages between Natives and Immigrants

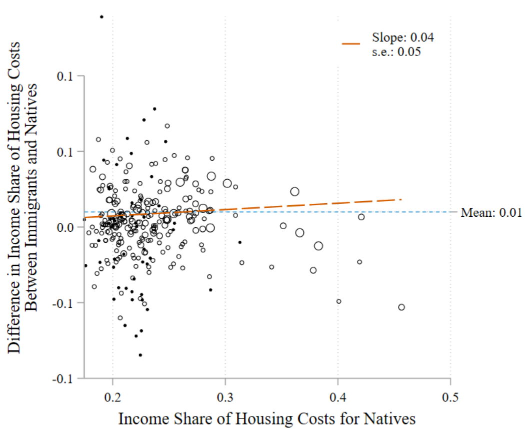
(a) Housing-Cost Differentials



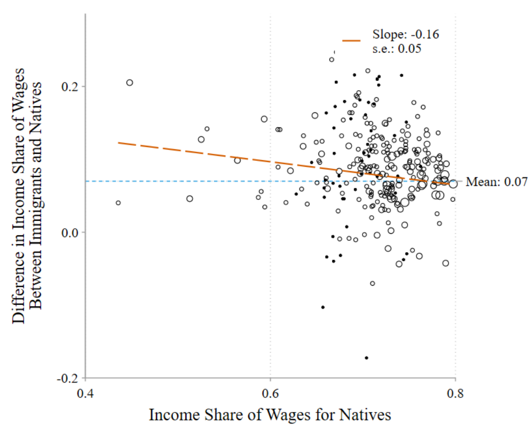
(b) Wage Differentials



(c) Income Share of Housing Costs

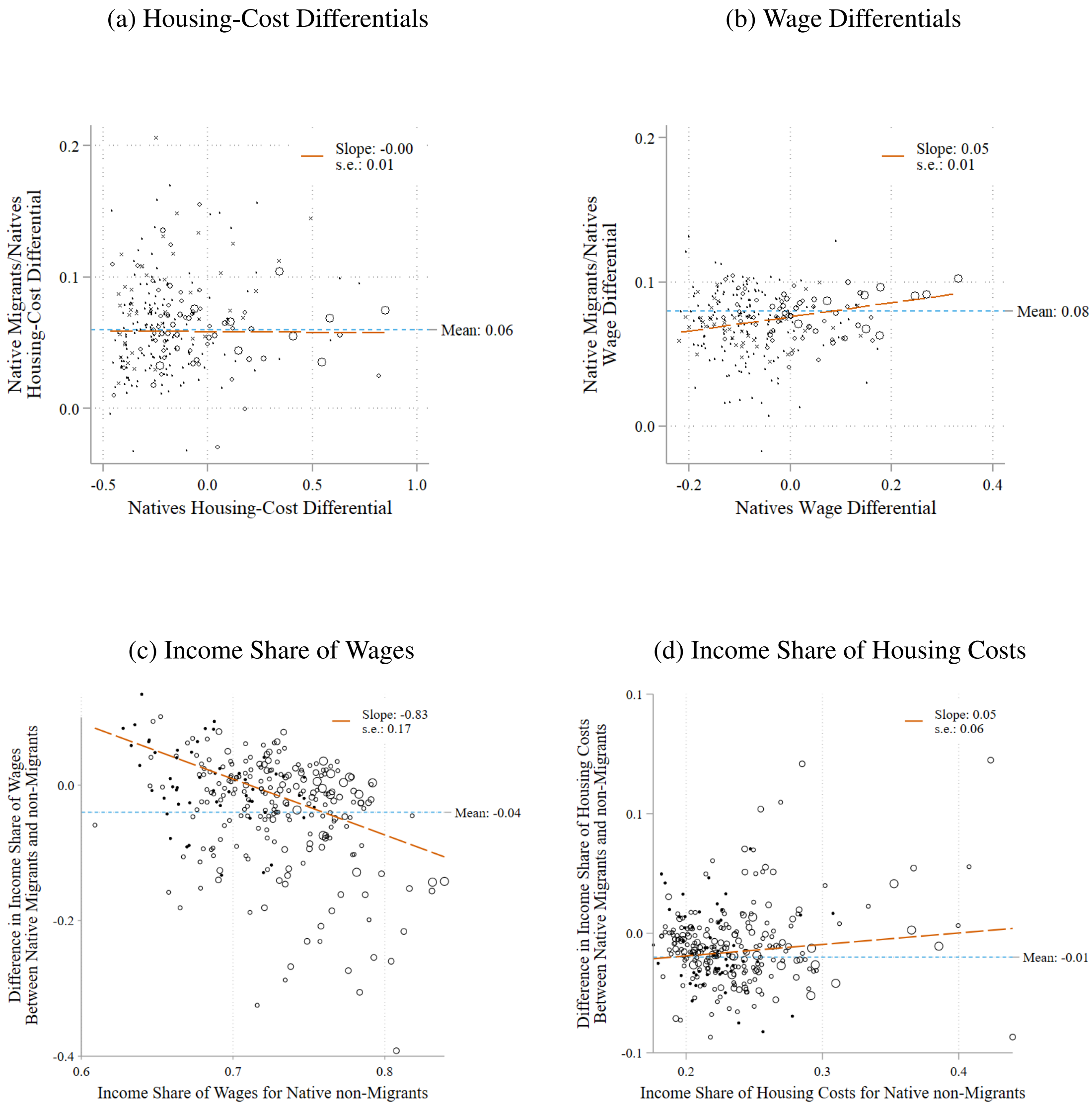


(d) Income Share of Wages



Notes: Observations are weighted by total metro population. Figure (a) has native housing-cost differential $\hat{p_j}^B$ on the X-axis and the difference between immigrant and native housing-cost differentials in the Y-axis: $\hat{p_j}^I - \hat{p_j}^B$. Figure (b) has native wage differential $\hat{w_j}^B$ on the X-axis and the difference between immigrant and native wage differentials in the Y-axis: $\hat{w_j}^I - \hat{w_j}^B$. Income share of wages is calculated as a fraction of wages of all household members in total household income.

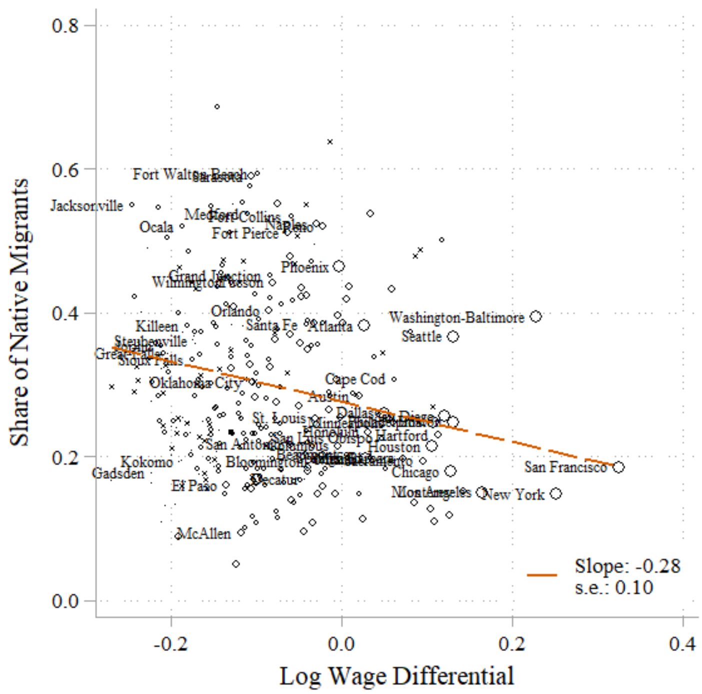
FIGURE A.3: Difference in Housing Cost and Wage Share of Income between Native Migrants and non-Migrants



Notes: Observations are weighted by total metro population. Income share of wages is calculated as a fraction of wages of all household members in total household income.

FIGURE A.4: Native Migrants Sorting on Price and Wage Differentials (2014)

(a) Wage Differentials



(b) Housing-Cost Differentials

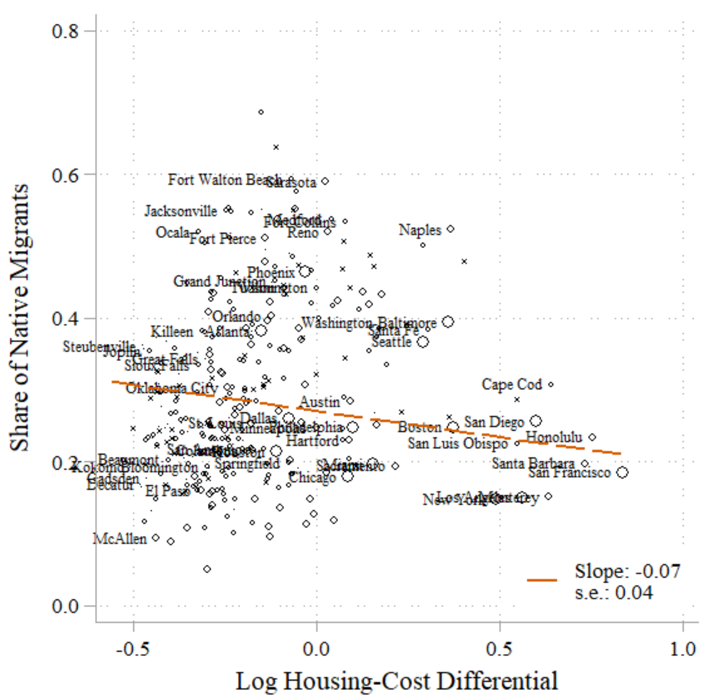
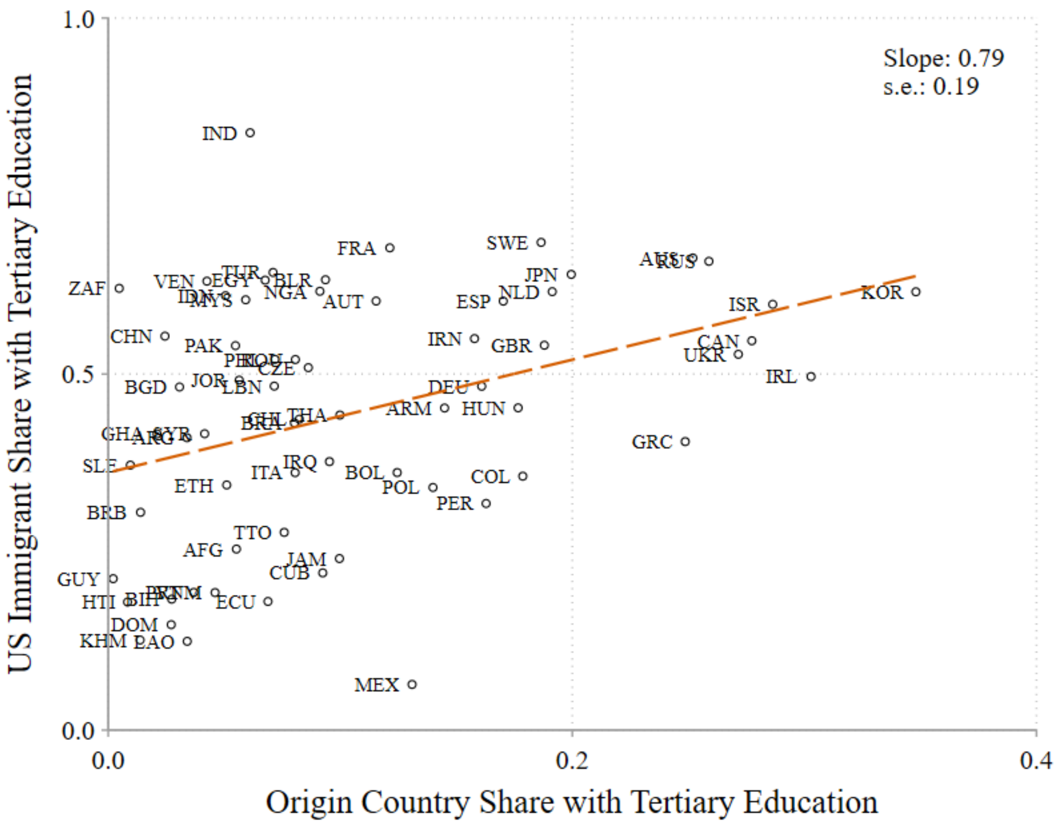


FIGURE A.5: Comparison of Education Attainment Measures



Notes: The X-axis is the Barro-Lee measure of educational attainment in countries of immigrant origin - percent of adult population with completed tertiary schooling. The Y-axis is the educational attainment of the U.S. immigrants by origin country - the share of adult population with at least an associate degree. The regression is unweighted.

TABLE A.1: Composition of Regions

Region	Countries
Latin America	Argentina Bolivia Brazil Chile Colombia Ecuador Guyana Peru Venezuela Barbados Cuba Dominican Republic Jamaica Haiti Trinidad and Tobago Mexico
Canada	Canada
Western and Northern Europe	United Kingdom Ireland Sweden Austria France Germany Netherlands
Southern and Eastern Europe	Greece Italy Portugal Czech Republic Hungary Poland Romania Belarus Russia Ukraine Bosnia and Herzegovina Serbia
Oceania	Australia and Oceania
South Central Asia	Afghanistan Bangladesh India Iran Pakistan

TABLE A.1: Composition of Regions - Continued

Region	Countries
Eastern and Southern Asia	China
	Japan
	South Korea
	Cambodia
	Indonesia
	Laos
	Malaysia
	Philippines
	Thailand
	Vietnam
Middle East and Northern Africa	Iraq
	Israel
	Jordan
	Lebanon
	Syria
	Turkey
	Armenia
	Egypt
Sub-Saharan Africa	Ethiopia
	South Africa
	Ghana
	Nigeria
	Sierra Leone

TABLE A.2: Immigrant Shares and Average Urban Amenities by Region

	Canada (3)	Latin America (4)	West/North Europe (5)	East/South Europe (6)	Oceania (7)
Cold Winter	8.09	0.57	5.43	5.60	1.49
Hot Summer	0.17	1.91	0.10	0.33	0.84
Sunshine	0.24	0.28	0.18	0.24	0.31
Close to Coast	0.11	0.45	0.50	0.35	0.83
Average Slope	0.37	0.76	0.33	0.59	0.18
Immigrant Share (2000)	0.26	5.36	0.66	0.98	0.03
Difference in Share (2014-2000)	0.00	0.40	-0.11	-0.16	0.01

	East/South Asia (8)	South Central Asia (9)	Middle East (10)	Sub-Saharan Africa (11)
Cold Winter	1.99	0.81	2.17	0.26
Hot Summer	2.15	2.73	1.35	1.27
Sunshine	0.24	0.30	0.36	0.27
Close to Coast	0.66	0.19	0.46	0.30
Average Slope	0.60	0.36	0.96	0.92
Immigrant Share (2000)	1.98	0.60	0.30	0.21
Difference in Share (2014-2000)	0.51	0.43	0.05	0.11

Notes: Cold winter (hot summer) is measured with heating (cooling) degree days. These measures help to estimate the amount of energy to heat or cool a building to the human comfort temperature (65○F). Sunshine is population weighted (average sunshine time)/(total time). Close to coast measure is the share of population near ice-free coast or river (Gallup et al. (1998)). Average slope is population weighted Terrain Ruggedness Index (Nunn and Puga (2012)). Average regional measures are weighted by country population. If the data is available for multiple cities, population weighted country average is calculated first.

TABLE A.3: Household Data Summary Statistics, Pooled 2000-2014

	Weighted by native pop.	Weighted by immigrant pop.	Correlation with the same measure for native migrants
Housing cost differential			
Immigrants	-0.04	0.11	.96
	(0.27)	(0.30)	
Native migrants	0.12	0.30	
	(0.29)	(0.31)	
Difference between	-0.15	-0.19	-0.59
immigrants and native migrants	(0.09)	(0.08)	
Wage differential			
Immigrants	-0.16	-0.13	0.83
	(0.10)	(0.09)	
Native Migrants	0.12	0.20	
	(0.13)	(0.12)	
Difference between	-0.29	-0.33	-0.66
immigrants and native migrants	(0.07)	(0.06)	
Housing cost as a share of income			
Immigrants	0.24	0.27	0.95
	(0.05)	(0.06)	
Native migrants	0.23	0.25	
	(0.05)	(0.06)	0.94
Difference between	0.01	0.01	0.02
immigrants and native migrants	(0.02)	(0.02)	
Wage share of income			
Immigrants	0.80	0.81	0.64
	(0.06)	(0.04)	
Native migrants	0.72	0.71	
	(0.06)	(0.07)	
Difference between	0.08	0.09	-0.52
immigrants and native migrants	(0.05)	(0.04)	
Willingness-to-pay			
Immigrants	0.01	0.04	0.79
	(0.06)	(0.07)	
Natives	0.00	0.02	
	(0.05)	(0.06)	

Notes: Standard errors are in parentheses. We pool the 2000 and 2014 (2012-2016) data. Wage share of income is measured as a fraction of wages of all household members in total household income. Correlation coefficient is calculated using total metro population as weights.

TABLE A.4: Characteristics of Immigrants, Native Migrants and Natives in Birth States

	Immigrants		Native Migrants		Natives in Birth State	
	2000	2014	2000	2014	2000	2014
Share of Population	11.1	13.3	29.3	28.1	59.6	58.6
Male	49.8	48.7	48.6	48.9	49.1	49.5
Married	56.4	56.6	50.9	46.8	36.2	30.9
Avg. Age	39.1	44.2	42.0	45.0	32.2	33.5
Avg. Number of Children	0.97	0.96	0.60	0.52	0.48	0.41
Homeowner	51.1	53.0	70.0	66.3	72.2	66.9
Graduate Degree	8.2	10.7	9.2	12.1	3.7	5.0
College Degree	11.5	15.3	15.7	18.8	8.2	10.6
Some College	13.5	15.9	20.0	22.5	14.2	17.8
High School Degree	17.9	19.3	21.6	17.8	21.9	18.8
Less Than High School	45.0	33.2	26.5	19.1	46.7	39.8

Notes: Graduate degree is defined as master's, professional (beyond bachelor's) or doctoral degree. College degree is defined as bachelor's degree. Some college is defined as associate's degree or one or more years of college without a degree. High school is defined as high school diploma or GED. Rows 1-3 and 6-11 are in percent. The number of children in the household is the number of own children of all ages living with respondents.

TABLE A.5: Probit Regression Results

	P(Native Migrant)	P(Native Migrant)
	2014	2000
	(1)	(2)
Female	-0.0379***	-0.0196***
	(0.001)	(0.001)
Graduate Degree	0.00693***	0.0383***
	(0.002)	(0.003)
College Degree	0.116***	0.214***
	(0.002)	(0.002)
Some College	0.182***	0.257***
	(0.002)	(0.002)
High School Degree	0.0189***	0.170***
	(0.002)	(0.002)
Black	-0.512***	-0.286***
	(0.002)	(0.002)
Hispanic	-1.600***	-1.669***
	(0.002)	(0.002)
Asian	-2.374***	-2.375***
	(0.002)	(0.003)
Indigenous	0.377***	0.459***
	(0.008)	(0.009)
Other Race (Non-White)	-0.425***	-0.329***
	(0.003)	(0.003)
Age 15-17	0.232***	0.0396***
	(0.004)	(0.004)
Age 18-20	0.160***	-0.121***
	(0.004)	(0.004)
Age 21-24	-0.034***	-0.339***
	(0.003)	(0.003)
Age 25-29	-0.195***	-0.407***
	(0.003)	(0.003)
Age 30-34	-0.311***	-0.428***
	(0.003)	(0.003)
Age 35-39	-0.399***	-0.385***
	(0.003)	(0.003)
Age 40-44	-0.401***	-0.346***
	(0.003)	(0.003)
Age 45-49	-0.360***	-0.313***
	(0.003)	(0.003)
Age 50-54	-0.295***	-0.297***
	(0.002)	(0.003)
Age 55-59	-0.233***	-0.276***
	(0.002)	(0.003)
Age 60-64	-0.201***	-0.350***
	(0.003)	(0.003)
Age 65 plus	-0.190***	-0.309***
	(0.003)	(0.004)
Pseudo R^2	0.337	0.342

Notes: Standard errors are in parentheses. The sample includes immigrants and native cross-state migrants only.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.6: Reweighted Immigrant and Native Migrant Sorting by Prices, Wages and Urban Attributes

	Log Odds		Enclave	Log Odds		Enclaves
	Enclaves excluded	Enclaves included		Enclaves excluded	Enclaves included	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reweighted Immigrants						
Wage	-2.40	-0.51	-5.07**			
	(4.34)	(3.78)	(2.06)			
Housing Cost	3.13***	1.79***	3.59***			
	(1.10)	(0.68)	(0.70)			
Immigrants Predicted by 1980 Enclaves		0.37*			0.37*	
		(0.19)			(0.19)	
Trade-Productivity				2.92	2.54	1.02
				(3.52)	(3.49)	(1.22)
Willingness-to-Pay				8.62**	4.74*	10.52***
				(3.84)	(2.53)	(2.39)
R^2	0.31	0.36	0.45	0.31	0.36	0.45
Panel B: Native Migrants (Cross State)						
Wage	-2.77***	-1.65**	-1.58**			
	(0.86)	(0.68)	(0.66)			
Housing Cost	0.69*	0.02	0.96***			
	(0.36)	(0.38)	(0.20)			
Native Migrants Predicted by 1980 Enclaves		0.71***			0.70***	
		(0.10)			(0.10)	
Trade-Productivity				-1.91***	-1.76***	-0.22
				(0.61)	(0.34)	(0.48)
Willingness-to-Pay				2.96**	0.81	3.06***
				(1.18)	(1.19)	(0.73)
R^2	0.13	0.42	0.11	0.14	0.43	0.11
Panel C: Difference between Immigrants and Native Migrants (p-score)						
Wage	0.85	0.49	0.03			
Housing Cost	0.00	0.00	0.00			
Enclaves		0.01			0.01	
Trade-Productivity				0.01	0.01	0.29
Willingness-to-Pay				0.00	0.00	0.00

Notes: Robust standard errors(in parentheses) are clustered by metro areas. We add year indicators in all columns. Regressions are weighted by metro immigrant population in Panel A and metro native population in Panel B. Refer to Section 5.1 for the way to construct the reweighted immigrant sample.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.7: Immigrant Sorting by Urban Attributes, Heterogeneity

	All	Young	Single	High Edu	Recent Migrants	Reweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Immigrants (coefficients)						
Trade-Productivity	0.71	1.01	0.54	1.70*	1.09	2.92
	(1.08)	(0.83)	(1.03)	(0.91)	(0.90)	(3.52)
Willingness-to-Pay	5.87***	4.56***	5.58***	5.72***	3.40***	8.62**
	(1.58)	(1.39)	(1.45)	(1.25)	(1.29)	(3.84)
R^2	0.36	0.32	0.36	0.60	0.36	0.31
Panel B: Difference between the Opposite Immigrant Group (p-score)						
Trade-Productivity		0.26	0.12	0.00	0.21	
Willingness-to-Pay		0.00	0.05	0.39	0.00	

Notes: Robust standard errors (in parentheses) are clustered by metro. Regressions are weighted by metro immigrant population. Dependent variable is the log odds of each immigrant subgroup. Subgroups used in the regressions are presented in column titles. Young (1) refers to age less than 50. Single (2) refers to not married, separated or divorced. High Edu (3) refers to some college or more. Recent migrants (4) refer to arriving in U.S. less than 10 years ago. Reweighted (5) refers to reweighted immigrants that resemble native migrants in their observable characteristics. Panel B tests for the difference between the opposite immigrant groups (columns 2-5) by reporting p-scores. ***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.8: Immigrant and Native Migrant Sorting and the Value of Amenities, Excluding Metros in California and Florida

	Willingness-to-Pay		Log Odds	
	Enclaves excluded	Enclaves included	Enclaves excluded	Enclaves included
	(1)	(2)	(3)	(4)
Panel A: Immigrants				
Logarithm of Metro Population	0.011**	0.007	0.280***	0.168***
	(0.005)	(0.004)	(0.041)	(0.040)
Warm Winters	0.018**	0.020***	0.085	0.142***
[base 65, minus heating degree days]	(0.007)	(0.007)	(0.087)	(0.044)
Mild Summer	0.075***	0.075***	-0.073	-0.078
[base 65, minus cooling degree days]	(0.015)	(0.016)	(0.203)	(0.128)
Sunshine	0.299***	0.256***	1.968*	0.719
[out of percent possible]	(0.083)	(0.080)	(1.142)	(0.748)
Close to Coast	0.003***	0.003***	0.004	-0.012*
[miles, minus square root of distance]	(0.001)	(0.001)	(0.009)	(0.007)
Average Slope of Land	0.002	0.000	0.122***	0.067***
[percent]	(0.003)	(0.003)	(0.033)	(0.020)
Close to Ports of Entry	0.001	0.000	0.033***	0.010
[miles, minus square root of distance]	(0.001)	(0.001)	(0.007)	(0.006)
Safety	0.086*	0.070*	0.484*	0.014
[minus number of violent crimes per 1,000]	(0.048)	(0.041)	(0.286)	(0.198)
Percent Tertiary Degree	0.398***	0.471***	-0.413	1.680**
	(0.076)	(0.056)	(1.178)	(0.658)
Wharton Land Use Regulatory Index	-0.007	-0.010**	0.116**	0.025
	(0.004)	(0.004)	(0.055)	(0.049)
Immigrants Predicted by 1980 Enclaves		0.015**		0.418***
[log odds]		(0.007)		(0.051)
R^2	0.70	0.72	0.75	0.87
Panel B: Native Migrants (Cross State)				
Logarithm of Metro Population	-0.008***	-0.008***	-0.055**	-0.041*
	(0.003)	(0.003)	(0.028)	(0.025)
Warm Winters	0.022***	0.023***	0.305***	0.201***
[base 65, minus heating degree days]	(0.005)	(0.005)	(0.057)	(0.051)
Mild Summer	0.040***	0.041***	0.225*	0.104
[base 65, minus cooling degree days]	(0.011)	(0.011)	(0.128)	(0.111)
Sunshine	0.270***	0.279***	3.031***	1.661*
[out of percent possible]	(0.055)	(0.062)	(0.868)	(0.876)
Close to Coast	0.001	0.001	-0.010	-0.012**
[miles, minus square root of distance]	(0.001)	(0.001)	(0.008)	(0.005)
Average Slope of Land	0.005**	0.005**	-0.004	-0.006
[percent]	(0.002)	(0.002)	(0.022)	(0.020)
Close to Ports of Entry	0.001	0.001	-0.024**	-0.020***
[miles, minus square root of distance]	(0.001)	(0.001)	(0.009)	(0.007)
Safety	0.030	0.029	-0.120	0.066
[minus number of violent crimes per 1,000]	(0.019)	(0.019)	(0.155)	(0.155)
Percent Tertiary Degree	0.311***	0.313***	3.181***	2.812***
	(0.048)	(0.047)	(0.766)	(0.458)
Wharton Land Use Regulatory Index	0.005	0.005	-0.028	-0.011
	(0.004)	(0.004)	(0.031)	(0.029)
Native Migrants Predicted by 1980 Enclaves		-0.003		0.473***
[log odds]		(0.007)		(0.068)
R^2	0.52	0.53	0.65	0.76

Notes: Robust standard errors (in parentheses) are clustered by metro area. All columns include the latitude and year indicators. The dependent variables in columns 1 and 2 are willingness-to-pay of immigrants (Panel A) and native migrants (Panel B). The dependent variables in columns 3 and 4 are log odds of immigrants (Panel A) and native migrants (Panel B). Columns 2 and 4 additionally include immigrant enclave (Panel A) and native migrant enclave (Panel B) measures. Regressions are weighted by metro immigrant population in Panel A, and by metro native population in Panel B. 37 percent of immigrant metro population are living in metros located in California and Florida (2000 and 2014), and they are excluded from the anlysis.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.9: Immigrant and Native Migrant Sorting and the Value of Amenities, by Years in the U.S.

	Willingness-to-Pay		Log Odds	
	Enclaves excluded	Enclaves included	Enclaves excluded	Enclaves included
	(1)	(2)	(3)	(4)
Panel A: Immigrants in US for More than 10 Years				
Logarithm of Metro Population	0.019***	0.013***	0.295***	0.124***
	(0.003)	(0.003)	(0.023)	(0.032)
Warm Winters	-0.008*	-0.006	0.015	0.073**
[base 65, minus heating degree days]	(0.005)	(0.004)	(0.058)	(0.034)
Mild Summer	0.021***	0.015**	-0.077	-0.234***
[base 65, minus cooling degree days]	(0.008)	(0.007)	(0.123)	(0.079)
Sunshine	0.052	-0.008	2.394**	0.808
[out of percent possible]	(0.076)	(0.066)	(0.950)	(0.636)
Close to Coast	0.004***	0.003***	0.018**	-0.004
[miles, minus square root of distance]	(0.001)	(0.001)	(0.008)	(0.007)
Average Slope of Land	0.005**	0.002	0.132***	0.069***
[percent]	(0.002)	(0.002)	(0.029)	(0.018)
Close to Ports of Entry	0.000	-0.001	0.029***	0.013***
[miles, minus square root of distance]	(0.001)	(0.001)	(0.005)	(0.003)
Safety	0.064*	0.051	0.146	-0.224
[minus number of violent crimes per 1,000]	(0.034)	(0.031)	(0.315)	(0.200)
Percent Tertiary Degree	0.217***	0.317***	-2.067***	0.583
	(0.059)	(0.062)	(0.731)	(0.538)
Wharton Land Use Regulatory Index	0.005	0.002	0.181***	0.093**
	(0.004)	(0.004)	(0.054)	(0.044)
Immigrants Predicted by 1980 Enclaves		0.015***		0.408***
[log odds]		(0.005)		(0.047)
R^2	0.70	0.72	0.82	0.90
Panel B: Immigrants in US for Less than 10 Years				
Logarithm of Metro Population	0.021***	0.013**	0.198***	0.074**
	(0.005)	(0.006)	(0.022)	(0.031)
Warm Winters	-0.012	-0.010	0.053	0.095***
[base 65, minus heating degree days]	(0.008)	(0.007)	(0.044)	(0.030)
Mild Summer	0.036***	0.029**	-0.203**	-0.317***
[base 65, minus cooling degree days]	(0.012)	(0.012)	(0.088)	(0.063)
Sunshine	0.237**	0.167*	0.744	-0.408
[out of percent possible]	(0.107)	(0.101)	(0.692)	(0.507)
Close to Coast	0.006***	0.005***	-0.005	-0.021***
[miles, minus square root of distance]	(0.001)	(0.001)	(0.007)	(0.006)
Average Slope of Land	0.006*	0.003	0.098***	0.053***
[percent]	(0.003)	(0.003)	(0.024)	(0.017)
Close to Ports of Entry	-0.001	-0.001	0.025***	0.014***
[miles, minus square root of distance]	(0.001)	(0.001)	(0.004)	(0.003)
Safety	0.021	0.005	-0.252	-0.521***
[minus number of violent crimes per 1,000]	(0.039)	(0.037)	(0.265)	(0.191)
Percent Tertiary Degree	0.306***	0.422***	1.132*	3.057***
	(0.095)	(0.098)	(0.631)	(0.520)
Wharton Land Use Regulatory Index	0.001	-0.003	0.120***	0.056
	(0.006)	(0.006)	(0.045)	(0.044)
Native Migrants Predicted by 1980 Enclaves		0.018**		0.296***
[log odds]		(0.008)		(0.043)
R^2	0.70	0.71	0.74	0.81

Notes: Robust standard errors (in parentheses) are clustered by metro area. All columns include the latitude and year indicators. The dependent variables in columns 1 and 2 are willingness-to-pay of immigrants who are in the U.S. for more than 10 years (Panel A) and who are in the U.S. for less than 10 years (Panel B). The dependent variables in columns 3 and 4 are log odds. Columns 2 and 4 additionally include immigrant enclaves. Regressions are weighted by metro immigrant population.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.10: Immigrant Enclaves and Amenities

	Log Odds of Immigrant Enclaves (1)	Log Odds of Native Migrants Enclaves (2)
Logarithm of Metro Population	0.421***	-0.049*
	(0.038)	(0.028)
Warm Winters	-0.142	0.077
[base 65, minus heating degree days]	(0.088)	(0.055)
Mild Summer	0.384**	-0.100
[base 65, minus cooling degree days]	(0.172)	(0.087)
Sunshine	3.890***	1.426**
[out of percent possible]	(1.359)	(0.562)
Close to Coast	0.055***	0.016*
[miles, minus square root of distance]	(0.013)	(0.010)
Average Slope of Land	0.153***	0.040
[percent]	(0.051)	(0.027)
Close to Ports of Entry	0.038***	-0.013**
[miles, minus square root of distance]	(0.007)	(0.006)
Safety	0.908**	-0.551***
[minus number of violent crimes per 1,000]	(0.458)	(0.176)
Percent Tertiary Degree	-6.499***	1.739**
	(1.054)	(0.758)
Wharton Land Use Regulatory Index	0.217**	-0.005
	(0.089)	(0.045)
R^2	0.78	0.23

Notes: Robust standard errors are shown in parentheses. All columns control for the latitude and include year indicators. Regressions are weighted by immigrant population in column 1 and native population in column 2.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.11: Immigrants, Native Migrants and Reweighted Immigrants Sorting and the Value of Individual Amenities

Dependent Vairable : Log Odds	Immigrants (1)	Immigrants (2)	Native Migrants (3)	Native Migrants (4)	Reweighted (5)	Reweighted (6)
Logarithm of Metro Population	0.284***	0.111***	-0.122***	-0.094***	0.466***	0.347**
	(0.024)	(0.033)	(0.034)	(0.030)	(0.122)	(0.147)
Warm Winters	0.032	0.090***	0.101**	0.056*	-0.381**	-0.340**
[base 65, minus heating degree days]	(0.059)	(0.034)	(0.047)	(0.033)	(0.162)	(0.147)
Mild Summer	-0.118	-0.276***	-0.455***	-0.396***	-0.730***	-0.839***
[base 65, minus cooling degree days]	(0.123)	(0.079)	(0.101)	(0.104)	(0.237)	(0.232)
Sunshine	2.019**	0.421	-0.009	-0.845	2.077	0.973
[out of percent possible]	(0.943)	(0.634)	(0.665)	(0.610)	(2.072)	(1.828)
Close to Coast	0.010	-0.012*	-0.008	-0.018***	0.066**	0.051**
[miles, minus square root of distance]	(0.008)	(0.007)	(0.008)	(0.006)	(0.028)	(0.025)
Average Slope of Land	0.129***	0.066***	0.020	-0.004	0.189***	0.145***
[percent]	(0.029)	(0.018)	(0.025)	(0.023)	(0.059)	(0.052)
Close to Ports of Entry	0.030***	0.015***	-0.028***	-0.020***	0.048**	0.038
[miles, minus square root of distance]	(0.005)	(0.004)	(0.006)	(0.005)	(0.023)	(0.024)
Safety	0.075	-0.298	-0.362**	-0.040	-1.157	-1.415*
[minus number of violent crimes per 1,000]	(0.314)	(0.193)	(0.170)	(0.159)	(0.778)	(0.757)
Percent Tertiary Degree	-1.249*	1.422**	4.504***	3.485***	0.486	2.331
	(0.740)	(0.558)	(0.723)	(0.512)	(2.275)	(2.630)
Wharton Land Use Regulatory Index	0.170***	0.081*	0.008	0.011	0.329**	0.268*
	(0.057)	(0.048)	(0.043)	(0.038)	(0.149)	(0.146)
Log Odds of Enclaves		0.411***		0.586***		0.284*
		(0.049)		(0.068)		(0.145)
R^2	0.80	0.89	0.53	0.70	0.68	0.69

Notes: Robust standard errors are shown in parentheses. All columns control for the latitude and include year indicators. Regressions are weighted by metro immigrant population. ***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.12: Immigrant Sorting and the Value of Individial Amenities, by Sub-regions

	Latin America (1)	East/Southeast Asia (2)	South Central Asia (3)	East/South Europe (4)	West/North Europe (5)	Middle East (6)	Sub Saharan Africa (7)	Canada (8)	Oceania (9)
Logarithm of Metro Population	0.32***	0.18***	0.24***	0.18***	0.03	0.31***	0.25***	-0.06*	-0.09*
	(0.04)	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)
Warm Winters	-0.12	0.36***	0.25***	-0.11	-0.02	-0.17*	-0.08	-0.10	0.71***
[base 65, minus heating degree days]	(0.09)	(0.05)	(0.07)	(0.08)	(0.04)	(0.09)	(0.09)	(0.07)	(0.08)
Mild Summer	-0.13	0.34***	0.16	-0.31***	-0.14**	0.21***	-0.33*	-0.50***	0.27*
[base 65, minus cooling degree days]	(0.13)	(0.13)	(0.10)	(0.10)	(0.07)	(0.08)	(0.19)	(0.07)	(0.16)
Sunshine	2.44**	3.01***	0.42	1.33	0.93*	2.25***	-1.76	1.28**	2.92**
[out of percent possible]	(1.22)	(0.91)	(0.56)	(0.96)	(0.52)	(0.75)	(1.22)	(0.58)	(1.30)
Close to Coast	0.00	0.01	-0.02	0.03**	0.03***	0.05***	0.00	0.06***	-0.07***
[miles, minus square root of distance]	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Average Slope of Land	0.16***	0.03	-0.06	0.02	0.08***	-0.04	-0.12*	0.12***	0.10
[percent]	(0.04)	(0.03)	(0.05)	(0.03)	(0.02)	(0.04)	(0.07)	(0.01)	(0.07)
Close to Ports of Entry	0.04***	0.01***	0.03***	0.03***	0.01*	-0.02**	-0.02**	-0.02***	0.04***
[miles, minus square root of distance]	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Safety	0.48	-0.13	-0.19	-0.09	-0.06	-1.41**	0.08	-0.41	0.45
[minus number of violent crimes per 1,000]	(0.38)	(0.22)	(0.25)	(0.31)	(0.16)	(0.55)	(0.48)	(0.40)	(0.45)
Percent Tertiary Degree	-5.02***	2.95***	3.02***	-0.38	3.19***	0.15	7.74***	2.81**	1.26
	(1.07)	(0.57)	(0.92)	(1.35)	(0.58)	(0.99)	(1.75)	(1.19)	(1.23)
Wharton Land Use Regulatory Index	0.21**	-0.04	-0.01	0.14*	0.08**	0.02	0.06	0.18***	0.06
	(0.09)	(0.05)	(0.05)	(0.08)	(0.04)	(0.08)	(0.13)	(0.07)	(0.08)
R^2	0.75	0.90	0.81	0.78	0.66	0.67	0.66	0.56	0.75
Share of Immigrants	0.511	0.192	0.074	0.069	0.052	0.031	0.030	0.021	0.005

Notes: Robust standard errors are clustered by metro area. Regressions weighted by total immigrant population from each origin country. For the detailed list of countries for each sub-region, refer to Table A.1. Urban attributes are calculated using the methodology from Albouy (2016), restricting samples to immigrants.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.13: Natives, Native Migrants and Amenities

	Willingness -to-Pay of Natives (1)	Willingness -to-Pay of Native Migrants (2)
Logarithm of Metro Population	-0.001	-0.004
	(0.003)	(0.003)
Warm Winters	0.015***	0.015***
[base 65, minus heating degree days]	(0.004)	(0.004)
Mild Summer	0.036***	0.033***
[base 65, minus cooling degree days]	(0.006)	(0.006)
Sunshine	0.235***	0.211***
[out of percent possible]	(0.047)	(0.047)
Close to Coast	0.002***	0.002***
[miles, minus square root of distance]	(0.001)	(0.001)
Average Slope of Land	0.006***	0.006***
[percent]	(0.002)	(0.002)
Close to Ports of Entry	0.001	0.000
[miles, minus square root of distance]	(0.001)	(0.001)
Safety	0.037**	0.039**
[minus number of violent crimes per 1,000]	(0.016)	(0.017)
Percent Tertiary Degree	0.277***	0.315***
	(0.047)	(0.046)
Wharton Land Use Regulatory Index	0.006**	0.006*
	(0.003)	(0.003)
	-0.071	-0.007
R^2	(0.062)	(0.059)
	0.73	0.70

Notes: Robust standard errors shown in parentheses. All columns include the latitude and year indicators. Regressions are weighted by metro native population.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.14: Unweighted Push Regression

Dependent Variable: Log of Immigrant Population	Country Level			Metro Level
	(1)	(2)	(3)	(4)
Logarithm of Origin Country Population	0.44***		0.45***	0.53***
	(0.07)		(0.09)	(0.08)
Logarithm of Per Capita GDP	0.55		0.81	-0.41
	(0.62)		(0.64)	(0.77)
Logarithm of Per Capita GDP, Squared	-0.04		-0.05	0.03
	(0.04)		(0.04)	(0.04)
Logarithm of Distance to USA	-1.53***		-1.44***	-0.95***
	(0.20)		(0.22)	(0.28)
Warm Winters		0.04	0.01	-0.03
[Minus Heating Degree Days]		(0.10)	(0.07)	(0.08)
Mild Summers		-0.23	-0.13	-0.30*
[Minus Cooling Degree Days]		(0.18)	(0.16)	(0.17)
Close to Coast		0.21	0.57	0.06
[Percent Pop 100km from Coast]		(0.44)	(0.41)	(0.46)
Average Slope		0.13	0.33	0.45*
[Population Weighted TRI]		(0.23)	(0.25)	(0.24)
Sunshine		-4.40**	-2.44	-3.50**
[Percentage of Available Sunshine Time]		(2.01)	(1.79)	(1.69)
Safety		-0.11	0.02	0.09
[Minus Number of Homicides Per 10,000]		(0.09)	(0.07)	(0.07)
Education Attainment		4.00*	2.57*	2.08
[Percentage of Tertiary Schooling]		(2.15)	(1.39)	(1.45)
Adjusted R^2	0.45	0.08	0.49	0.65
Number of Observations	130	130	130	29073
Number of Countries	65	65	65	
Metro Fixed Effects				Y

Notes: Robust standard errors are clustered by origin country in columns 1 to 3 and clustered by metro and origin country in column 4.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.15: Immigrant Locations and Interaction between Destination City and Origin Country Amenities: A ”Push-Pull” Model of Migration

Dependent Variable: Log Odds of Immigrant	(1)	(2)	(3)	(4)
Logarithm of Country Population	0.73***			
	(0.07)			
Logarithm of Per Capita GDP	0.69			
	(1.03)			
Logarithm of Per Capita GDP2	-0.04			
	(0.06)			
Logarithm of Distance to USA	-1.27***			
	(0.16)			
Warm Winters	0.23**			
[Minus Heating Degree Days]	(0.11)			
Mild Summers	-0.39			
[Minus Cooling Degree Days]	(0.23)			
Close to Coast	1.39**			
[Percent Pop 100km from Coast]	(0.64)			
Average Slope	0.35			
[Population Weighted TRI]	(0.35)			
Sunshine	-5.99			
[Percentage of Available Sunshine Time]	(5.71)			
Percent Tertiary Education	10.26**			
	(4.07)			
Safety	0.28***			
[Minus Number of Deaths Per 10,000]	(0.10)			
Warm Winters [Country] X Warm Winters [Metro]	0.04**	0.04**	0.04**	0.02**
	(0.02)	(0.02)	(0.02)	(0.01)
Mild Summer [Country] X Mild Summer [Metro]	-0.04	-0.05	-0.04	-0.03
	(0.08)	(0.09)	(0.08)	(0.03)
Close to Coast [Country] X Close to Coast [Metro]	2.62	2.25	2.44	1.40
	(9.90)	(10.93)	(10.78)	(9.12)
Average Slope [Country] X Average Slope [Metro]	0.32**	0.32**	0.33**	0.04
	(0.15)	(0.15)	(0.15)	(0.07)
Sunshine [Country] X Sunshine [Metro]	0.14	0.14	0.15	0.12*
	(0.13)	(0.13)	(0.14)	(0.07)
Minus Homicide Rates [Country] X Minus Violent Crime Rates [Metro]	0.21**	0.17	0.18	0.16***
	(0.09)	(0.11)	(0.12)	(0.05)
Percent Tertiary Education [Country] X Percent Tertiary Education [Metro]	-16.24*	-7.04**	-9.30***	-9.04***
	(8.88)	(2.84)	(2.30)	(2.76)
Percent Tertiary Education [US Immigrants] X Percent Tertiary Education [Metro]			6.03***	4.40***
			(1.21)	(1.18)
R^2	0.67	0.76	0.76	0.77
Number of Observations	28830	28830	28830	22105
Number of Countries	65	65	65	50
Metro Fixed Effects	Y	Y	Y	Y
Country Amenities Controls	Y			
Country Fixed Effects		Y	Y	Y
Excludes Latin American Immigrants				Y

Notes: Robust standard errors are clustered by metro and origin country. Regressions are weighted by the predicted number of immigrants from each origin country in each metro. All columns include year indicators. We include controls for country-level amenities in column 1 and country fixed effects in column 2.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.

TABLE A.16: Immigrant Locations and Interaction between Destination City and Origin Country Amenities: A "Push-Pull" Model of Migration (Homicide Rates instead of Violent Crime Rates)

Dependent Variable: Log Odds of Immigrant	(1)	(2)	(3)	(4)
Warm Winters	0.04**	0.04**	0.04**	0.02**
[Home Country × Destination City]	(0.02)	(0.02)	(0.02)	(0.01)
Mild Summer	-0.04	-0.05	-0.04	-0.03
[Home Country × Destination City]	(0.09)	(0.09)	(0.08)	(0.03)
Close to Coast	2.72	2.36	2.56	1.58
[Home Country × Destination City]	(9.90)	(10.93)	(10.79)	(9.11)
Average Slope	0.32**	0.32**	0.32**	0.04
[Home Country × Destination City]	(0.15)	(0.15)	(0.15)	(0.07)
Sunshine	0.14	0.14	0.15	0.12*
[Home Country × Destination City]	(0.13)	(0.14)	(0.14)	(0.07)
Safety	0.98	0.95	0.97	1.20**
[Home Country × Destination City]	(0.82)	(0.95)	(1.01)	(0.53)
Percent Tertiary Education	-16.29*	-7.27**	-9.54***	-9.02***
[Home Country × Destination City]	(8.93)	(2.85)	(2.27)	(2.76)
Percent Tertiary Education			5.99***	4.40***
[Immigrants from Same Country × Destination City]			(1.19)	(1.18)
R^2	0.67	0.76	0.76	0.77
Number of Observations	28830	28830	28830	22105
Number of Countries	65	65	65	50
Metro Fixed Effects	Y	Y	Y	Y
Country Amenities Controls	Y			
Country Fixed Effects		Y	Y	Y
Excludes Latin American Immigrants				Y

Notes: Robust standard errors are clustered by metro and origin country. Regressions are Weighted by the predicted number of immigrants from each origin country in each metro. All columns include year indicators. We include controls for country-level amenities in column 1 and country fixed effects in column 2. For the safety measure, we interact homicide rates of U.S. cities with homicide rates of origin countries.
***; **; * indicate significance at the 1%; 5%; 10% level, respectively.