The Impact of Immigration on Wages, Internal Migration and Welfare

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Abstract

This paper studies the impact of immigration on wages, internal migration and welfare. Using U.S. Census data, I estimate a spatial equilibrium model where labor differs by skill level, gender and nativity. Workers are heterogeneous in city preferences. Cities vary in productivity levels, housing prices and amenities. I use the estimated model to assess the distributional consequences of several immigration policies. The results show that a skill selective immigration policy leads to welfare gains for low skill workers, but welfare losses for high skill workers. The negative impacts are more substantial among the incumbent high skill immigrants. Internal migration mitigates the initial negative impacts, particularity in cities where housing supplies are inelastic. However, the negative wage impacts on some workers intensify. This is because an out-migration of workers of a given type may raise the local wages for workers of that type, while reducing the local wages of workers with complementary characteristics. Overall, there are substantial variations in the welfare effects of immigration across and within cities. Further, I use the model to assess the welfare effects of the border wall between Mexico and the U.S. The results show that the potential benefits are significantly smaller than the proposed cost of construction.

Keywords: Immigration, worker heterogeneity, local labor markets, welfare impact.

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1 Introduction

Increased migration into the U.S. in the past few decades has raised concerns partly because of its magnitude and its composition. Over the first half of the past decade, around 1.25 million immigrants arrived each year (Card, 2009). The share of immigrants in the U.S. working-age population increased from 10 percent in 1990 to about 17 percent in 2007.[1] At least a third of the new immigrants are undocumented with little education and limited English skills (Passel, 2005). A key political debate in the U.S. centers around controlling the number and composition of immigrants, leading to proposed policies such as building a border wall between the U.S. and Mexico and reforming the program of high skill immigrant visas. This raises the questions of who would lose and who would gain from these policies?

Many studies focus on the national impacts of immigration (e.g. Borjas, 2003 and Ottaviano and Peri, 2012). However, local impacts may differ from national impacts since some cities attract relatively more immigrants. The immigrant share of the working-age population in the U.S. varies from more than 40 percent, for example in Los Angeles and Miami, to roughly two percent in cities such as Flint, MI. An inflow of immigrants may reduce wages for competing workers and raise wages for complementary labor. However, wages may not represent the full welfare effects as any wage gains may be offset, or losses amplified, by rising housing costs due to immigration. Heterogeneity in city characteristics, such as housing supply elasticities and amenities, could lead to greater real welfare inequality across workers.

Moreover, an inflow of new arrivals may induce internal migration which could modify the local impact and transmit immigration shocks to other cities. While previous works suggest that internal mobility attenuates adverse local shocks (e.g. Borjas, 2001, Borjas, 2006 and Cadena and Kovak, 2016), the effects are likely to be heterogeneous across workers. This is because an out-migration of workers of a given type may raise the local wages for workers of that type, while reducing the local wages of workers with complementary characteristics. For instance, if high and low skill labor are complements, then an outflow of high skill workers may reduce the local wages of low skill workers. Thus, even within a city, workers can be affected by immigration differently due to heterogeneity in labor types and degrees of internal mobility.

Given the linkage between cities through labor relocation, I study the welfare implications of immigration using a spatial equilibrium model. I use the estimated model to assess changes in the skill mix and stock of immigrants as well as the benefits of the border wall between the U.S. and Mexico. I quantify the wage and welfare effects of immigration on different groups of workers across cities both when workers are constrained to remain in their original locations and when all

[1] Source: 1990-2000 U.S. Census and the combined 2005-7 ACS. Working-age population includes people aged 18 or older with 1 to 40 years of potential experience. See 2.1 for further details.

workers are free to migrate. I also quantify the increased rental income accruing to landlords, a potential benefit that is often not included in welfare analysis of immigration.

The present framework is built on Diamond (2016) who decomposes welfare inequality between college and noncollege workers from changes in city characteristics: wages, rents and amenities. In her paper, the counterfactual change in each city characteristic is assumed to be independent with no equilibrium effects on other city characteristics, and labor is only differentiated by skill levels: high and low.[2] To assess the impact of immigration across local labor markets, I extend the framework from Diamond (2016) in two dimensions. First, I incorporate heterogeneity across workers in skill level, gender and birthplaces. Since the impacts of immigration are likely to depend on the degree of substitutability of labor, I allow for the possibility that workers of different types are imperfect substitutes. Cities differ in productivity levels, housing supply elasticities, and amenities. Preferences for city characteristics are heterogeneous across types of workers. Second, I modify the model to allow the value of a city among immigrants to depend on their networks in that city. A well-known settlement pattern of immigrants is that they tend to locate in country-specific enclaves (Altonji and Card, 1991). Therefore, to capture this pattern, I use the number of previous immigrants born in the same country to represent the strength of the network. I also allow the value of a city among natives to depend on the distance from the city to the individual's birthplace. Finally, in my counterfactual policy experiments, I measure welfare allowing wages, rents and location choices to adjust simultaneously.

I estimate the model using U.S. Census data from 1980 through 2000 and the combined 2005-7 American Community Survey. I estimate local labor demand in multiple steps using the Card and Lemieux (2001) technique. The elasticities of substitution are identified using the predicted inflow rate of immigrants based on historical settlement patterns (Altonji and Card, 1991). Labor supply is estimated using the discrete choice methods developed by McFadden (1973), Berry et al. (1995) and Berry et al. (2004) which have been applied to estimate workers' preferences for locations by Bayer et al. (2007) and Diamond (2016). I adapt their approach and identify workers' preferences using local labor demand shocks driven by the city's industry mix. The housing supply elasticity is identified using the interaction of these shocks with housing supply elasticity determinants which provide variation in housing demand (Diamond, 2016).

The estimates indicate imperfect substitutability between natives and immigrants within the same skill-gender group. The substitutability between natives and immigrants is lower among high

[2] Diamond (2016)'s welfare decomposition involves computing the expected counterfactual utility change driven by the 1980 to 2000 changes in each city's characteristics: (i) wage, (ii) rent, (iii) local endogenous amenities. The counterfactual change in each city characteristic is treated to be completely independent, i.e. a change in a city's wage has no equilibrium impact on the city's and other cities' rents or endogenous amenities, and vice versa. She finds that differences in local amenities lead to an increase in well-being inequality between college and noncollege workers much larger than the increase in the college wage gap alone.

skill than low skill workers. High skill workers are estimated to be less attached to their birthplaces and networks, relative to low skill workers. Further, in line with Borjas (2001) Cadena and Kovak (2016) and Diamond (2016), immigrants are more sensitive to changes in prices than natives. These estimates imply that cities with more previous immigrants or natives who already left their birthplaces are more likely to experience an out-migration response to immigration since these workers are relatively mobile. Additionally, cities with (i) lower productivity, (ii) more inelastic housing supply or (iii) lower amenities are more likely to have an outflow of incumbent workers.

The estimated model allows me to consider three relevant counterfactual policy experiments. First, I consider the effects of the U.S. adopting a skill-selective immigration policy similar to the UK, leading to a 46 percent increase in high skill immigrants. I find that the average wages of low skill workers initially rise by about 4 percent in gateway cities which receive a larger portion of the new high skill immigrants, while the average wages of low skill workers in other cities rise, on average, by around $1-2$ percent. The wage increase is due to the complementarity between high and low skill labor. There are small positive effects on the wages of high skill natives in most locations, while the wages of incumbent high skill immigrants fall substantially in all locations. The differential wage impacts between immigrants and natives is due to their imperfect substitutability. I find that a one percent increase in a city's population due to immigration is associated with approximately a one percent increase in average housing rents.

Since both changes in wages and rents impact migration decisions, I illustrate how migration responses can alter the overall distributional impact by focusing on local real wages. As workers relocate, the immigration impact becomes more equalized across cities, particularly for high skill workers. The local real wages of high skill workers tend to improve in cities with inelastic housing supply as high skill workers out-migrate to more affordable cities. While the out-migration responses mitigate the adverse wage effects for workers of that type, they also reduce the wages of workers with complementary characteristics. Therefore an out-migration response of high skill workers, while reducing rents for all stayers, can lead to a smaller net benefit on local real wages for low skill workers.

The gains from internal migration realized by the movers in gateway cities are equivalent to a 500 to $1,000$ dollar increase in annual consumption. The additional rental income accruing to landlords is sizable. Overall, even after worker relocation, the welfare impact of immigration is unevenly distributed across and within cities, re-emphasizing the importance of studying the welfare consequences of immigration at the local labor market level.

In the second counterfactual policy experiment, I assume that the U.S. maintains its present skill composition of immigrants but increases the stock by the same number as in the first counterfactual. This involves a 25 percent increase in immigrants. The arrival of new immigrants has more positive wage effects on high skill natives and less negative wage effects on high skill immigrants relative to the first counterfactual. This is because a larger portion of new immigrants in this counterfactual are low skill, and so the negative wage effect is counterbalanced by the complementarity between high and low skill labor. The wages and welfare of low skill natives decline.

However, when all workers are free to migrate, the negative impacts in some cities attenuate. The migration responses of low skill workers in this counterfactual are more pronounced. This is because the most adversely affected group in this experiment is low skill immigrants. The out-migration responses of low skill workers substantially reduce the initial negative wage and rent impacts in inelastic housing supply cities such as Miami, while intensifying the negative wage impacts in more affordable cities. The gains from internal migration of movers are about 50 percent smaller than in the first counterfactual, and the additional rental income accruing to landlords is about 30 percent smaller.

The final policy experiment examines the effects of the border wall between the U.S. and Mexico. The massive construction cost, as proposed by the Trump administration (Meckler, 2018), calls into question whether the benefits would outweigh the cost. I simulate the effects of the wall on wages, rents and welfare under a range of scenarios when different fractions of an inflow of potentially illegal immigrants from Mexico in the states adjacent to Mexico are removed. The results show that, even if the wall were to reduce the inflow of potentially illegal immigrants by 80%, the benefits would still be significantly lower than the cost of construction.

This paper contributes to the literature on immigration. Early studies on the effects of immigration analyze the wage impact (e.g. Borjas, 2003, Card, 1990 and Ottaviano and Peri, 2012) separately from the rent impact (e.g. Saiz, 2007).[3] However, both of these prices affect welfare and location choices. Most importantly, the effects vary across cities. As emphasized in works on local labor markets, accounting for heterogeneity in city characteristics is crucial for measuring real welfare (Moretti, 2013, David et al., 2013, David and Dorn, 2013 and Diamond, 2016). While internal migration plays a vital role in mitigating local shocks (e.g. Blanchard et al., 1992, Borjas, 2001 and Cadena and Kovak, 2016 and Monras, 2015), this paper highlights the importance of taking into account heterogeneity in the labor types of movers and stayers. The main contribution is to quantify the welfare impacts of immigration by integrating these key different channels in a spatial equilibrium model. I show that an analysis based on wages or local real wages alone does not provide a complete representation of the distributional consequences on welfare. Further, I characterize the types of cities that are helped or hurt by different immigration policies.

The rest of the paper is organized as follows: Section 2 presents an overview of the data.

[3]Early studies on the wage effects of immigration provide mixed conclusions. Borjas et al. (1996) and Borjas (2003) document that immigration has a pronounced negative effect on natives' wages while Card (1990) and Ottaviano and Peri (2012) find little impact. Card (2009) argues that the discrepancy between these findings is reconciled by recognizing the high-degree of substitutability between high school graduates and dropouts as well as the imperfect substitutability between natives and immigrants.

Section 3 specifies the model and Section 4 describes the estimation procedures. Section 5 presents the baseline results. Section 6 shows counterfactual experiments and Section 7 concludes.

2 Data Overview

2.1 Sample Description

The analysis is based on data from the five percent samples of the 1980, 1990 and 2000 U.S. Census as well as the combined 2005-7 American Community Surveys (ACS) from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2010). Throughout the analysis, I refer to the combined 2005-7 ACS as the 2007 sample period.

The key characteristics of workers are skill level, gender and nativity. I define "cities" as the metropolitan statistical areas (MSA's) from the 2000 Census. I use information on definitions of MSAs at the detailed level to match the 2000 MSAs to 1980 and 1990. The ACS uses the same geographic coding as the 2000 Census. The Census includes 218 MSAs consistently across the three rounds. I focus on the 114 MSAs which have at least 200 full-time and non self-employed of each type of immigrants based on the key characteristics described above.[4] I combine other areas together and treat them as the outside option. The outside option can be regarded as the combined non-popular destinations of immigrants, relative to other cities, where its characteristics are taken to be the average characteristics of these combined areas.[5]

Workers in the sample are restricted to individuals over the age of 18 with 1 to 40 years of potential experience who report positive earnings and worked at least one week in the previous year and not currently enrolled in schools.[6] High skill workers are defined as those with 1-3 years of college or more. Low skill workers include high school graduates and dropouts. This classification of two skill groups is supported by Card (2009) who estimate the inverse elasticity of substitution between dropouts and high school graduates, and the inverse elasticity of substitution between workers with some college and those with a college degree or more to be near zero. Immigrants are defined as individuals born abroad.

The wage sample is a subset of the employment sample where workers who are self-employed and workers who work less than 35 hours a week and 40 weeks a year are eliminated. Additional data on land use regulations and geographic constraints are taken from Saiz (2010). The main esti-

[4] All MSAs have at least 200 full-time and non self-employed natives in each skill-gender cell.

[5] While the analysis could be richer by treating each MSA and the rural part of each state as a separate location choice, the numbers of immigrants in those areas are too low to identify the parameters of interest. Further, I do not have data on land use regulations and the shares of land unavailable for construction in all rural areas to estimate their housing supply functions.

[6] Years of potential experience are calculated using the difference between current age and the age at which the individual entered the labor force.

mation of labor demand, labor supply and housing supply uses prices and employment information from the 1990 and 2000 U.S. Census, and the combined 2005-7 ACS. The 1980 U.S. Census is only used for constructing instrumental variables, network effects and the predetermined population in the housing rent equation. See Appendix A. for further details on variable construction and Table A.1 for summary statistics of these variables.

2.2 Characteristics and Settlement Patterns of Immigrants

The motivation for the city-level analysis in this paper is illustrated in Table A.2, which presents immigrant densities in the 15 most popular destinations of immigrants. The immigrant shares of the working-age population in these cities range from about 30 to 60 percent. Further, cities that attract more immigrants in 1990 continue to attract more immigrants over time.

Table A.3 in the Online Appendix reports the numbers and characteristics of immigrants from 1990-2007. The share of immigrants in the U.S. working-age population increased from about 10 percent in 1990 to 17 percent in 2007; the large inflow and the composition of immigrants has raised many concerns. More than half of immigrants have only high school diplomas or less. So local workers may be affected differently due to heterogeneity in labor types. Further, a well-known immigrant settlement pattern is that they tend to locate in country-specific enclaves (see Card, 2009 for more discussion). This suggests that country of origin is also an important characteristic determining location choices and the local impacts of immigration. Additionally, Table A.4 reports the numbers of immigrants and educational attainment by country of origin.

3 Model

To analyze the effects of immigration across local labor markets, I extend a static spatial equilibrium model of Diamond (2016) in two dimensions. First, I incorporate heterogeneity across workers in skill level, gender and nativity via a nested-CES technology. I allow for the possibility that workers of different types are imperfect substitutes.[7]

Cities differ in productivity levels, housing prices and amenities. Preferences for city characteristics may vary across worker types. Housing supply elasticities differ across cities due to differences in geographic constraints. Second, to account for immigrants' tendency to locate in the same regions as their fellow expatriates, I extend the model to allow immigrants to derive utility from cities' networks. I use the number of previous immigrants born in the same country group in the past to represent the strength of the network.[8] Additionally, I allow the value of a city amongst

[7] Diamond (2016) assumes that immigrants and natives are perfect substitutes; this assumption restricts immigrants and natives to bear the same effects of immigration on their wages.

[8] Without the presence of network effects, it would be difficult to replicate the enclave pattern of immigrants.

natives of the same type to depend on the distance between that location and their birthplaces.

I begin this section by specifying labor demand, then discuss workers' location decisions, housing supply, and finally present the equilibrium conditions.

3.1 Labor Demand

To derive simple expressions for city-specific labor demand, I assume a one-sector economy. While I do not explicitly incorporate multiple sectors into the model, I allow cities' production functions to differ in productivity to reflect differences in cities' sectoral compositions. Firms are competitive and produce identical tradeable goods using capital and labor with a constant returns technology.[9] Each city c has many homogeneous firms in year t. In what follows, I drop the firm's subscript for ease of exposition. The firm's production function takes the following form

$$Y_{ct} = A_{ct} L_{ct}^{\alpha} K_{ct}^{1-\alpha} \tag{1}$$

where A_{ct} is city-specific productivity, K_{ct} is capital, L_{ct} is a CES aggregate of different types of labor, and $\alpha \in (0,1)$ is the income share of labor.[10]

An immigrant is defined as a person born outside the U.S. Since workers are heterogeneous, the effects of immigration depends on the substitutability between labor types and the magnitude of the inflow. Intuitively, immigrants may put downward pressure on the wages of substitute labor and upward pressure on the wages of complements. The model incorporates imperfect substitution amongst labor inputs via a nested CES production function similar to Ottaviano and Peri (2012).[11] There are two main differences between my setup and Ottaviano and Peri (2012). First, I allow male and female labor to be imperfect substitutes. Given that males and females tend to work in different occupations, their imperfect substitutability captures occupational differences across genders in this single national product setup.[12] As reported in Johnson and Keane (2013), unconditional on occupations, the substitutability between men and women is low. Second, I do not differentiate workers by age since I focus on long run equilibrium where workers make location choices in a static setting.[13] The CES nests are ordered by skill, gender and nativity. I place skill

[9] As estimated by Basu and Fernald (1997), production functions in most industries exhibit roughly constant returns to scale. Using plant-level data, Baily et al. (1992) find that firms produce with approximately constant returns technology.

[10] The alternative is to allow complementarity between capital and labor as in Krusell et al. (2000); however, data on capital at the city level is restricted.

[11] Manacorda et al. (2012) use a similar nested-CES production function as Ottaviano and Peri (2012) to study the national impact of immigration in the UK.

[12] An alternative is to distinguish types of workers by occupation or major of study. However, the counterfactual exercises involve solving for an equilibrium allocation of workers across cities. Therefore, I abstract from the substitutability between labor of different occupations to keep the number of worker types computationally manageable.

[13] I provide a sensitivity analysis of labor demand estimation when wages are residualized against age in Section

levels in the upper nests since education seems to be the primary determinant of labor substitutability. I put gender in the second level and place workers' immigration status in the last level.[14]

The first-level nest of labor aggregate is a combination of high and low skill labor according to

$$L_{ct} = \left(\sum_{e} \theta_{ect} L_{ect}^{\rho_E} \right)^{\frac{1}{\rho_E}}, \tag{2}$$

where the skill levels are high and low $e \in \{H, L\}$, and $\sigma_E = \frac{1}{1-\rho_E}$ is the elasticity of substitution between skill levels. The parameters $\theta_{Hct}, \theta_{Lct}$ represent the relative productivity levels of high and low skill labor, respectively.[15] These may vary over time due to skill-biased technical change. Further, the relative productivity levels at each CES level may vary across cities. This is to reflect variation in cities' productivities based on differences in industrial compositions. I normalize $\theta_{Hct} + \theta_{Lct} = 1$ and similarly for the relative productivity levels in the lower CES levels; any common multiplying factor is absorbed in A_{ct}.

This classification of two skill groups is commonly used (see for example Katz and Murphy, 1992 and Card and Lemieux, 2001). The alternative is to have four skill groups: college, some college, high school and dropouts (Borjas, 2003). However, as noted in Card (2009) and Ottaviano and Peri (2012), the inverse elasticities of substitution between college and some college, as well as between high school graduates and dropouts are approximately zero.

At the next level, the skill-specific labor L_{ect} is a CES aggregate of male and female labor

$$L_{ect} = \left(\sum_{g} \phi_{egct} L_{egct}^{\rho_G} \right)^{\frac{1}{\rho_G}}, \tag{3}$$

where $g \in \{F, M\}$ denotes female and male respectively, $\phi_{eFct} + \phi_{eMct} = 1$, and $\sigma_G = \frac{1}{1-\rho_G}$ is the elasticity of substitution between genders. The parameters ϕ_{eFct}, ϕ_{eMct} vary by skill level, city and over time. Johnson and Keane (2013) estimate that conditional on education and occupation, men and women are close substitutes. However, the unconditional substitutability between genders is low.

Finally, L_{egct} is a combination of labor supplied by natives, L_{egnct} and immigrants, L_{egmct}. I allow the elasticity of substitution between natives and immigrants to vary across skill levels as

5.5.

[14]In Section 5.5, I provide a sensitivity analysis of labor demand estimation when the order of skill and gender levels are reversed.

[15]A concern with assigning skill levels of workers based on their educational levels is that immigrants may be downgraded, e.g. an immigrant with a Bachelor degree may be working in a low skill occupation. See Dustmann et al. (2013) for more discussion.

follows

$$L_{egct} = \left(\sum_{s} \beta^{s}_{egct} L^{\rho_{M,E}}_{egsct} \right)^{\frac{1}{\rho_{M,E}}}, \tag{4}$$

where $s \in \{m,n\}$ denotes immigrant and native, respectively, $\beta^{n}_{egct} + \beta^{m}_{egct} = 1$, and $\sigma_{M,E} = \frac{1}{1-\rho_{M,E}}$ denotes the elasticity of substitution between natives and immigrants in each skill level. I allow for the possibility that immigrants might be closer substitutes to natives amongst low skill labor since factors such as differences in the quality of education and English skills may be less crucial. Further, the relative productivity levels between natives and immigrants, $\beta^{n}_{egct}, \beta^{m}_{egct}$ are allowed to vary by skill, gender, city and time. This allows wages of natives relative to immigrants in a specific group and city to vary over time due to changes in the cohort quality of immigrant labor.

I focus on long run equilibrium where capital is perfectly elastically supplied at a common priceκ_t. Let P_t denote the output price. Firms operate in a perfectly competitive output market so real wages equal the marginal product of labor. The city's demands for workers of characteristics: (e,g,s) in city c in year t is given by

$$\begin{aligned} \ln W^{s}_{egct}/P_t \quad = \quad & \frac{1}{\alpha}\ln A_{ct} + \ln\eta_t + \ln\theta_{ect} + \frac{1}{\sigma_E}\left(\ln L_{ct} - \ln L_{ect}\right) + \ln\phi_{egct} \\ & + \frac{1}{\sigma_G}\left(\ln L_{ect} - \ln L_{egct}\right) + \ln\beta^{s}_{egct} + \frac{1}{\sigma_{M,E}}\left(\ln L_{egct} - \ln L_{egsct}\right) \end{aligned} \tag{5}$$

and

$$\eta_t = \ln\left(\alpha \left(\frac{(1-\alpha)}{\kappa_t/P_t} \right)^{\frac{1-\alpha}{\alpha}} \right).$$

3.2 City Amenity and Network

In reality, cities differ in many dimensions. To better understand how individuals make their location decisions, I allow cities to differ in amenities. This includes climate as well as the quality of goods and services. All residents within a city have access to these amenities, but different groups of workers do not need to value these amenities equally. The amenities in city c in year t are denoted by x^{A}_{ct}.

A well-known settlement pattern of new immigrants is that they tend to locate in country-specific enclaves (Card, 2009).[16] This could be because it is easier to move or adjust to a city where an individual has a larger network.[17] Therefore, I consider the utility value an immigrant gains

[16] Prominent examples include the concentration of Arab immigrants in Detroit (see Abraham, 2000) and Mexican immigrants in Los Angeles and Chicago.

[17] Curran and Rivero-Fuentes (2003) and Massey and Espinosa (1997) find that networks affect immigration decisions. Additionally, Munshi (2003) documents that a Mexican immigrant is more likely to find a job in the U.S. if his network is larger.

from a city-specific network size. I use the city's number of previous immigrants born in the same country group as a proxy for network size. The network values are exogenous, i.e. independent of the current number of immigrants; I make this assumption to reduce the multiplicity of equilibria. Intuitively, we can think of the number of previous immigrants as a proxy for the availability of place-specific information as well as ethnic goods and services. Furthermore, given the enclave patterns of immigrants in the data, holding the network strength fixed enables us to pin down an equilibrium that is likely to realize. Define $x^n_{c,t-\tau}$ as a 22 element vector where each component contains city c's number of immigrants in year $t-\tau$ born in each of the 22 country groups (see Table A.4 for the list of 22 country groups).

For natives, I allow workers to derive the network values from living in their birthplaces. Since I only observe birthplaces at the state level, I allow natives to gain utility from living in or near their states of birth (I also include U.S. outlying areas as natives' birth places: American Samoa, Guam, Puerto Rico and U.S. Virgin Islands). Define x^{st}_c as a 54 element vector where each component k is equal to one if part of city c is contained in state k. For natives who live outside their birth states, the network value depends on the distance from one's birth state to the destination city. Define x^d_c as a 54 element vector where each component k contains the distance from the population centroid in state k to the population centroid in city c. The vector of network value and amenities to worker i in city c in period t is

$$N_{ct} = \left(\mathbb{1}_{\{s=n\}}\left(x^{st}_c, x^d_c\right), \mathbb{1}_{\{s=m\}} x^n_{c,t-\tau}, x^A_{ct}\right) \tag{6}$$

where $\mathbb{1}_{\{s=n\}}$ and $\mathbb{1}_{\{s=m\}}$ are indicator functions equal one if a worker is native or immigrant, respectively.

3.3 Labor Supply

Each worker i chooses the most desirable location taking all cities' characteristics as given.[18] For simplicity, the original immigration decision is taken to be exogenous; upon arrival in the U.S., an immigrant must choose a city of residence. Natives are born and initially live in their birth locations. Upon entering the labor market, they choose a city of residence. In reality, immigration may affect the extensive margin of the natives' labor supply, at least in the short run in high immigrant density areas as documented in Card (2001) and Dustmann et al. (2016b) as well as the intensive margin as noted in Cortés and Tessada (2011).[19] However, the long run effects on the extensive and

[18] The present framework has eight types of workers and 115 locations. While the role of joint location decisions for couples is important, this requires estimating parameters for many possible types of households. Therefore, I leave this to future work.

[19] Card (2001) finds that the inflows of new immigrants into the U.S. between 1985-1990 reduced the employment rates of natives and earlier immigrants by up to 1 percentage point in most cities, and up to 3 percentage points in gateway cities. Dustmann et al. (2016b) study the employment effect of the inflow of Czech workers into Germany between 1990-1993, and find that this leads to a 0.9 percent decline in the employment of natives. However, the

intensive margins are likely to be modest (Beerli and Peri, 2016) and so, for tractability, I abstract from labor supply decisions.[20]

The worker maximizes utility by choosing a city c, the quantity of a housing good Q_t which has a local price of R_{ct}, and a national good G_t which has a common price of P_t. Let z denote a vector of the worker's characteristics which includes skill level $e \in \{H, L\}$, gender $g \in \{F, M\}$, and nativity $s \in \{m, n\}$. A worker of type z inelastically supplies one unit of labor and earns a wage of W_{ct}^z. The utility of worker i living in city c, U_{ict} is defined as

$$U_{ict} = \max_{Q,G} \ln\left(Q_{it}^{\lambda_z^r}\right) + \ln\left(G_{it}^{1-\lambda_z^r}\right) + u_i\left(N_{ct}\right) \tag{7}$$

subject to

$$P_t G_{it} + R_{ct} Q_{it} \leq W_{ct}^z$$

where $u_i(N_{ct})$ is the utility from city amenities and networks, $0 \leq \lambda_z^r \leq 1$ is a parameter which can be trivially identified as the share of income on housing. Most empirical studies find that housing is a normal good, with an income elasticity of $0.8 - 0.87$ (Polinsky and Ellwood, 1979). This suggests that housing expenditure shares may be lower for higher income workers. Since income inequality is most pronounced between college and noncollege workers (Katz and Autor, 1999), I restrict λ_z^r to only vary across skill-nativity groups.

Maximizing (7), the worker's indirect utility from living in city c in year t is given by

$$V_{ict} = w_{ct}^z - \lambda_z^r r_{ct} + u_i\left(N_{ct}\right) \tag{8}$$

where $w_{ct}^z = \ln\left(W_{ct}^z / P_t\right)$ and $r_{ct} = \ln\left(R_{ct}/P_t\right)$. The value of amenities and networks to worker i in city j in period t is defined as

$$u_i\left(N_{ct}\right) = \beta_z^A x_{ct}^A + \beta_{zt}^{st} st_i x_c^{st} + \beta_{zt}^d st_i x_c^d + \beta_{zt}^n n_i x_{c,t-\tau}^n + \lambda_z^\sigma \varepsilon_{ict} \tag{9}$$

where n_i is a 22 element binary vector with each component equal to one if the worker was born in the country group; and st_i is 54 element binary vector where each component equals one if the worker was born in the state. Each worker has an individual idiosyncratic taste for cities, ε_{ict} drawn from a Type I Extreme Value distribution. I assume that the variance of workers' idiosyncratic

employment response is largely driven by the decreased inflows of natives into work rather than the outflows.

[20]Focusing on the long run over a ten year period, Beerli and Peri (2016) find no effect of immigration on the employment rate of other workers. On the other hand, Cortés and Tessada (2011) find that the employment of low skill immigrants in services that are close substitutes for household production has led high skill women to change their labor supply decisions. High skill women at the top quartile of the wage distribution increased their average hours of work by 20 minutes per week and increased the probability of working more than 50 and 60 hours by 1.8 and 0.7 percentage points, respectively. However, there are no effects for women with wages below the median.

tastes for each city, worker i's marginal utility of the amenities β_z^A, and the value of networks $\beta_{zt}^{st}, \beta_{zt}^{d}, \beta_{zt}^{n}$ can vary across all types of workers. Furthermore, I allow the value of networks to vary across time for two reasons. First, this greatly simplifies the computation (see Section 4). Second, this allows the model to capture the cohort effects and account for the growth of immigrants into nontraditional cities.[21]

For identification purposes, I normalize the standard deviation of workers' idiosyncratic taste for cities to one by dividing (8) by λ_z^{σ}, and redefine the parameters of the normalized optimized utility function as

$$\begin{aligned} V_{ict} &= \lambda_z^w \left(w_{ct}^z - \lambda_z^r r_{ct} \right) \\ &\quad + \lambda_z^A x_{ct}^A + \lambda_{zt}^{st} st_i x_c^{st} + \lambda_{zt}^{d} st_i x_c^{d} + \lambda_{zt}^{n} n_i x_{c,t-\tau}^{n} + \varepsilon_{ict}. \end{aligned} \tag{10}$$

where $\left(w_{ct}^{z_i} - \lambda_z^r r_{ct} \right)$ is the worker's income net of housing expenditure or local real wage. Eq (10) can be rewritten as

$$V_{ict} = \Gamma_{ct}^z + \lambda_{zt}^{st} st_i x_c^{st} + \lambda_{zt}^{d} st_i x_c^{d} + \lambda_{zt}^{n} n_i x_{c,t-\tau}^{n} + \varepsilon_{ict}$$

where $\Gamma_{ct}^z = \lambda_z^w \left(w_{ct}^{z_i} - \lambda_z^r r_{ct} \right) + \lambda_z^A x_{ct}^A$ represents the mean utility of workers of type z from living in city c net of the home or network values. Since the preference shocks are drawn from an extreme value distribution, the probability of a person choosing to live in city c is

$$\Pr_{ict} = \frac{\exp\left(\Gamma_{ct}^z + \left(\lambda_{zt}^{st} st_i x_c^{st} + \lambda_{zt}^{d} st_i x_c^{d} + \lambda_{zt}^{n} n_i x_{c,t-\tau}^{n} \right) \right)}{\Sigma_{k \in C} \exp\left(\Gamma_{kt}^z + \left(\lambda_{zt}^{st} st_i x_c^{st} + \lambda_{zt}^{d} st_i x_c^{d} + \lambda_{zt}^{n} n_i x_{c,t-\tau}^{n} \right) \right)}. \tag{11}$$

Therefore the labor supplies for each worker type in city c in year t are

$$Z_{ct} = \Sigma_{i \in \mathscr{Z}_t} \Pr_{ict}$$

where Z_{ct} is the number of workers of type z in city c in year t, and $\mathscr{Z}_t$ is the set of workers of type z in the economy (McFadden, 1973).

3.4 Housing Market

Housing supply serves as a congestion force. While immigration may impact housing prices differently along the quality distribution, as documented in Saiz (2003), I focus on a simple model of homogeneous houses as in Saiz (2007) in order to reduce the dimension of choices made by the

[21] Kritz et al. (2013) document a rapid growth of immigrants into cities with historically small immigrant populations from 1980-2000; examples includes Atlanta, Dallas, Orlando, and Sacramento.

worker. The immigration effect on housing, in this case, should be interpreted as the city's average effect.

Each city is endowed with a fixed amount of land suitable for construction. Developers are price-takers and sell identical houses. Let $P_{h,ct}$ denote local hosing prices which are set through equilibrium in the competitive market. Following Davis and Palumbo (2008), the inputs to housing production include construction materials and land. Thorsnes (1997) estimates the elasticity of substitution between land and non-land inputs in the housing production to be around one. Therefore, I assume the housing production technology to take the following form

$$Q_{ct} = a_{ct}\ell_{ct}^{\varphi}m_{ct}^{1-\varphi},$$

where Q_{ct} is the quantity of houses in city c in year t, a_{ct} is city-specific productivity in the housing production, ℓ_{ct} is the amount of developable land and m_{ct} is the quantity of construction materials. The parameter φ represents the share of land in the housing production. The developer's profit function is

$$\pi = P_{h,ct}Q_{ct} - P_{\ell,ct}\ell_{ct} - P_{m,t}m_{ct},$$

where the price of construction materials $P_{m,t}$ is exogenous and the price of land $P_{\ell,ct}$ is a function of houses.[22] The land price takes the following form

$$P_{\ell,ct} = Q_{ct}^{\nu_c} \tag{12}$$

where ν_c measures the elasticity of land price. Since developers are price takers, and in the steady state equilibrium housing prices equal the discounted values of rents, we have the following housing supply equation

$$\ln(R_{ct}) \quad = \quad \ln(cc_{ct}) + \nu_c\varphi\ln Q_{ct} \tag{13}$$

where the construction cost $\ln cc_{ct} = \ln i_t + \ln\frac{1}{a_{ct}}\left[\left(\frac{\varphi}{1-\varphi}\right)^{1-\varphi} + \left(\frac{\varphi}{1-\varphi}\right)^{-\varphi}\right]P_{m,t}^{1-\varphi}$.

For simplicity, I assume that absentee landlords initially own and sell land to developers. Given workers' preferences in (7), the demand for local houses is given by

$$Q_{ct} = \sum_z Z_{ct}\frac{\lambda_z^r W_{ct}^z}{R_{ct}} \tag{14}$$

where Z_{ct} is the population of each worker type z living in city c year t. Substituting (14) into (13),

[22]The idea is that as a city expands, the land available for development decreases and hence land prices rise.

the equilibrium housing rent is determined by

$$\ln(R_{ct}) = \ln(CC_{ct}) + \gamma_c \ln\left(\sum_z Z_{ct}\lambda_z^r W_{ct}^z\right) \tag{15}$$

where $\ln CC_{ct} = (1/(1+\varphi v_c))\left(\ln i_t + \ln\frac{1}{a_{ct}}\left[\left(\frac{\varphi}{1-\varphi}\right)^{1-\varphi} + \left(\frac{\varphi}{1-\varphi}\right)^{-\varphi}\right]P_{m,t}^{1-\varphi}\right)$ is the equilibrium construction cost, and $\gamma_c = \frac{\varphi v_c}{1+\varphi v_c}$ measures the elasticity of rent with respect to housing demand.

The rent elasticity varies by geographic and regulatory constraints. Scarcity of land suitable for development limits new construction and leads to a more inelastic housing supply. I approximate γ_c as follows

$$\gamma_c = \gamma^{geo} x_c^{geo} + \gamma^{regu} \ln(x_c^{regu}). \tag{16}$$

In Eq (16), γ^{geo} measures the contribution of effective geographic constraints on the inverse elasticity of housing rent where x_c^{geo} measures the share of land within 50 km of each city's center that is unavailable for development.[23] The second term, γ^{regu} measures how variation in regulatory constraint x_c^{regu} impacts the inverse elasticity of housing supply. The 2005 Wharton Regulation Survey collected data on land use regulation; I use the Wharton Regulation Index (WRI) as a measure of regulatory constraints. Saiz (2010) provides these measures at the MSA level. Thus, the equilibrium housing rent is given by

$$\ln(R_{ct}) = \ln(CC_{ct}) + (\gamma^{geo} x_c^{geo} + \gamma^{regu} \ln(x_c^{regu})) \ln\left(\sum_z Z_{ct}\lambda_z^r W_{ct}^z\right). \tag{17}$$

3.5 Equilibrium

Equilibrium is defined by a set of prices (w_{ct}^{z*}, r_{ct}^*) and populations of each type (Z_{ct}^*) such that

1. Every worker i maximizes his or her utility by choosing the optimal city c^*:

$$c^* = \underset{j\in C}{\operatorname{argmax}} V_{ijt} \tag{18}$$

2. Every firm j chooses an optimal production plan y_{jt}^* to maximize its profit:

$$P_t^* Y_{jt}^* \geq P_t^* Y, \forall Y_{jt} \in \mathbf{Y}_{jt} \tag{19}$$

[23]This could be due to wetlands, water bodies or steep slopes.

3. The labor demand and labor supply of each worker type are equal:

$$Z_{ct}^{*} = \Sigma_{i\in\mathscr{Z}_t}\mathrm{Pr}_{ict} \tag{20}$$

$$\begin{aligned} w_{ct}^{z*} = {} & \frac{1}{\alpha}\ln A_{ct} + \ln\eta_t + \ln\theta_{ect} + \frac{1}{\sigma_E}\left(\ln L_{ct} - \ln L_{ect}\right) + \ln\phi_{egct} \\ & + \frac{1}{\sigma_G}\left(\ln L_{ect} - \ln L_{egct}\right) + \ln\beta_{egct}^{s} + \frac{1}{\sigma_{M,E}}\left(\ln L_{egct} - \ln Z_{ct}^{*}\right) \end{aligned} \tag{21}$$

4. Total local housing demand satisfies the housing rent equation

$$\ln\left(R_{ct}^{*}\right) = \ln\left(CC_{ct}\right) + \gamma_c \ln\left(\sum_{z} Z_{ct}^{*}\lambda_z^{r} W_{ct}^{z*}\right) \tag{22}$$

Under the assumptions that ε_{ict} is drawn from a Type I Extreme Value distribution which is continuous, and u_i as well as the firm's objective function are continuous, an equilibrium exists (see Appendix C. for the proof of existence). Bayer and Timmins (2005) show that the uniqueness of an equilibrium depends on the following features of the model: (i) the magnitude of the agglomeration and congestion forces; (ii) the total number of cities; (iii) the importance of individual tastes in the utility function; and (iv) the variation and importance of fixed attributes across cities such as home premiums and network values. A sufficiently strong agglomeration effect can change the preference rank-ordering of locations leading to multiple equilibria, while a congestion effect gives rise to a unique equilibrium by inducing workers to disperse which preserves the rank-order of locations. The present model incorporates a congestion force through housing supply. Further, network values are exogenous; hence there is no agglomeration incentive due to the current numbers of immigrants.[24] However, heterogeneity in labor types may induce complementary workers to concentrate in the same locations. Nonetheless, provided that the housing supply congestion effect is sufficiently strong, a unique equilibrium can be obtained (see Appendix C. for further discussion).

4 Estimation

The estimation consists of estimating the parameters of labor demand, worker preferences and housing rent equation, taking the observed prices and quantities in the data as the realized equilibrium. I estimate each part of the model separately and discuss identification below.

[24] I impose that the network effects are independent of the current number of immigrants to reduce the multiplicity of equilibria. However, since new immigrants tend to locate in the same regions as their fellow expatriates, holding the network strength fixed also enables us to pin down an equilibrium that is likely to realize.

4.1 Labor Demand

In general, the labor demand functions can be estimated in one step using nonlinear techniques. However, since the firm's production function takes a three-level nested CES form, estimating the parameters using a nonlinear system of equations generates numerical difficulties. Thus, I follow Card and Lemieux (2001) by proceeding iteratively from the lowest nest to the top.[25]

Step 1: Estimate immigrant-native parameters: β^{s}_{egct} and $\sigma_{M,E}$

Using (5), the relative wage of native to immigrant of given characteristics can be expressed as

$$\ln\left(\frac{W^{n}_{egct}}{W^{m}_{egct}}\right) = \ln\left(\frac{\beta^{n}_{egct}}{1-\beta^{n}_{egct}}\right) - \frac{1}{\sigma_{M,E}}\ln\left(\frac{L_{egnct}}{L_{egmct}}\right) + \xi_{egct} \tag{23}$$

where W^{n}_{egct} and W^{m}_{egct} are the average wages of natives and immigrants in group (g,e) in city c and year t. L_{egnct} and L_{egmct} are the numbers of employed natives and immigrants, respectively. ξ_{egct} represents other sources of variation in native-immigrant wage gaps. A concern with equation (23) is that ξ_{egct} may be correlated with the relative labor supply.[26] Therefore, I estimate (23) using an instrumental variable for the relative labor supply $\ln\left(\frac{L_{egnct}}{L_{egmct}}\right)$ (described in detail below).

As in Manacorda et al. (2012), (23) assumes that $\ln\left(\frac{\beta^{n}_{egct}}{1-\beta^{n}_{egct}}\right)$ varies additively as follows

$$\ln\left(\frac{\beta^{n}_{egct}}{1-\beta^{n}_{egct}}\right) = d_g + d_e + d_t + \gamma_p \log(\text{pop}_{1980}) + \gamma_\psi \psi_{1980} + \gamma_{KM}\text{KM}_{egct} \tag{24}$$

where d_g, d_e and d_t are the gender, education and time fixed effects, respectively. Additionally, I include $\log(\text{pop}_{1980})$, the log city size in 1980 and ψ_{1980}, the mean wage residuals in 1980 to capture any permanent city-specific factors, and estimates of the transitory shocks to the relative demand, KM_{egct}.[27] To measure transitory shocks KM_{egct}, I adapt an index of labor demand shifts proposed by Katz and Murphy (1992) which is also used in Moretti (2004a) and Notowidigdo (2011). The index represents shifts in the relative demand for different worker groups, predicted

[25] Other papers, e.g. Manacorda et al. (2012), also use this iterative estimation method.

[26] ξ_{egct} may contain unobserved factors in a city such as labor-augmenting productivity differences of immigrants relative to natives.

[27] Wage residuals are obtained from a linear regression model fit by gender, immigration status, age, age squared, skill level, ethnicity variables, and interactions of skill level with a measure of years in the U.S. of immigrants.

by a city's industrial composition. Formally, I define the Katz and Murphy (KM) index as[28]

$$\mathrm{KM}_{egct} = \sum_{i=1}^{ind} \omega_{i,c} \triangle L_{i,eg,-c,t} \tag{25}$$

where *ind* indexes three-digit industry, $\omega_{i,c}$ is the share of total hours worked in industry *ind* in city c in year $t-\tau$, and $\triangle L_{i,eg,-c,t}$ is the change in the log of total hours worked in the same industry nationally excluding workers in city c and workers in other cities in the given state, between $t-\tau$ and t by workers of type (g,e) in year t. I use the share of total hours in 1980, 1990 and 2000 for computing the KM indices in 1990, 2000 and 2007, respectively.

To address the endogeneity problem in (23), I instrument for the relative labor supply $\ln\left(\frac{L_{egnct}}{L_{egmct}}\right)$ using the predicted inflow rate of immigrants. Given the tendency of new immigrants to settle in country-specific enclaves, the number and city distribution amongst new arrivals are predictable (Altonji and Card, 1991). If $\triangle L_{egmjt}$ immigrants with characteristics (e,g) arrive from country j to the U.S. between year $t-5$ to t, then the predicted inflow rate as a fraction of the city's current population is given by

$$\triangle \hat{L}_{egmct} = \sum_j \left(L_{mjc,1980}/L_{mj,1980}\right) \triangle L_{egmjt}/P_c \tag{26}$$

where $L_{mj,1980}$ denotes the earlier population of immigrants from country j in the U.S. in 1980; $L_{mjc,1980}$ denotes the number living in city c in 1980; and P_c is the city's current population.[29] I estimate (23) using two-stage least squares weighted by population in each cell. The exclusion restriction is that the national inflow rates from each source country are exogenous to local conditions.[30] The inverse of the coefficients on the group-specific relative labor supply give estimates of the elasticities of substitution between immigrants and natives amongst high skill labor $\sigma_{M,H}$ and amongst low skill labor $\sigma_{M,L}$. The coefficients on the characteristics and city control variables provide estimates of each β^S_{egct}. Using these estimates, L_{egct} can be computed by (4).

Step 2: Estimate male-female parameters: ϕ_{egct} and σ_G

Similar to previous steps, I use (5) to compute the relative wages between gender separately for natives and immigrants. Given the estimates from step 1, the relative return to gender can be

[28] The term "Katz and Murphy" index is adopted from Moretti (2004a). This is similar to the Bartik instrument which measures local labor demand shifts using changes in the average national wages weighted by a city's industrial composition (Bartik, 2002).

[29] Eq (26) shows that the predicted inflow rate $\hat{L}_{egmct}$ is an average of the national inflow rates from each source country, weighted by the shares of the country's previous immigrants in city c.

[30] I discuss a concern that the initial immigrant shares may be correlated with unobserved factors in a city in Section 5.5.

expressed as

$$\ln\left(\frac{\hat{W}^s_{eMct}}{\hat{W}^s_{eFact}}\right) = \ln\left(\frac{\phi_{eMct}}{\phi_{eFct}}\right) - \frac{1}{\sigma_G}\ln\left(\frac{L_{eMct}}{L_{eFct}}\right) \tag{27}$$

where

$$\ln\left(\frac{\hat{W}^s_{eMct}}{\hat{W}^s_{eFct}}\right) = \ln\left(\frac{W^s_{eMct}}{W^s_{eFct}}\right) - \frac{1}{\sigma_{M,E}}\left(\ln\left(\frac{L_{eMct}}{L_{eFct}}\right) - \ln\left(\frac{L_{eMsct}}{L_{eFsct}}\right)\right) - \ln\left(\frac{\beta^s_{eMct}}{\beta^s_{eFct}}\right).$$

I assume that $\ln\left(\frac{\phi_{eMct}}{\phi_{eFct}}\right)$ varies additively as follows

$$\ln\left(\frac{\phi_{eMct}}{\phi_{eFct}}\right) = d_e + d_t + \pi_p \log(\text{pop}_{1980}) + \pi_\psi \psi_{1980} + \pi_{KM}\text{KM}_{ect}$$

where d_e, d_t are the education and time dummies, $\log(\text{pop}_{1980})$, the log city size in 1980 and ψ_{1980}, the mean wage residuals in 1980 capture permanent city-specific factor control variables as in step 1, and KM_{ect} measures the transitory shocks to the relative demand of the combined gender labor.[31] I estimate equation (27), weighted by population in each cell, using the predicted inflow rate of male immigrants $\hat{L}_{eMmct}$, defined in (26) as an IV. The estimates of σ_G, ϕ_{eMct} and ϕ_{eFct} allow us to compute L_{ect} using (3).

Step 3: Estimate high and low skill parameters: θ_{ect} and σ_E

Using (5), the relative returns to skill level can be expressed as

$$\ln\left(\frac{\hat{W}^s_{Hgct}}{\hat{W}^s_{Lgct}}\right) = \ln\left(\frac{\theta_{Hct}}{\theta_{Lct}}\right) - \frac{1}{\sigma_E}\ln\left(\frac{L_{Hct}}{L_{Lct}}\right), \tag{28}$$

where

$$\begin{aligned}\ln\left(\frac{\hat{W}^s_{Hgct}}{\hat{W}^s_{Lgct}}\right) = {} & \ln\left(\frac{W^s_{Hgct}}{W^s_{Lgct}}\right) - \frac{1}{\sigma_{M,H}}\left(\ln\left(\frac{L_{Hgct}}{L_{Hgsct}}\right)\right) + \frac{1}{\sigma_{M,L}}\left(\ln\left(\frac{L_{Lgct}}{L_{Lgsct}}\right)\right) - \ln\left(\frac{\beta^s_{Hgct}}{\beta^s_{Lgct}}\right) \\ & - \frac{1}{\sigma_G}\left(\ln\left(\frac{L_{Hct}}{L_{Lct}}\right) - \ln\left(\frac{L_{Hgct}}{L_{Lgct}}\right)\right) - \ln\left(\frac{\phi_{gHt}}{\phi_{gLt}}\right)\end{aligned}$$

can be computed using the estimates from previous steps. I approximate $\ln\left(\frac{\theta_{Hct}}{\theta_{Lct}}\right)$ as

$$\ln\left(\frac{\theta_{Hct}}{\theta_{Lct}}\right) = \chi_p \log(\text{pop}_{1980}) + \chi_\psi \psi_{1980} + d_t + \chi_{KM}\text{KM}_{ct}$$

[31] The KM index is computed similarly as in step 1 except that I combine hours of all workers within each skill group.

where d_t is the time dummies, $\log(\text{pop}_{1980})$, the log city size in 1980 and ψ_{1980}, the mean wage residuals in 1980 capture permanent city-specific factors, and KM_{ct} measures the transitory shocks to the relative demand.[32] I estimate equation (28) using the predicted inflow rate of high skill relative to low skill immigrants as an IV, defined similar to (26). The difference in this step is that the IV is the predicted ratio of high skill to low skill immigrants combining male and female workers ($\frac{\hat{L}_{Hmct}}{\hat{L}_{Lmct}}$). That is

$$\frac{\hat{L}_{Hmct}}{\hat{L}_{Lmct}} = \frac{\sum_j \left(L_{mjc,1980}/L_{mj,1980}\right) \triangle L_{Hmjt}/P_c}{\sum_j \left(L_{mjc,1980}/L_{mj,1980}\right) \triangle L_{Lmjt}/P_c}$$

where $\triangle L_{Hmjt}$ and $\triangle L_{Lmjt}$ denote the numbers of high and low skill immigrants arriving from country j to the U.S. between year $t-5$ to t, respectively. The rest of the notation is similar to (26).

Finally, Eq (5) implies that η_t and A_{ct} can be estimated as the time and city fixed effects as follows

$$\ln\left(\hat{W}^s_{egct}\right) = d_t + d_{ct}$$

where

$$\begin{aligned}
\ln\left(\hat{W}^s_{egct}\right) &= \ln\left(W^s_{egact}\right) - \frac{1}{\sigma_E}\left(\ln\left(L_{ct}\right)\right) - \ln\left(\theta_{ect}\right) \\
&\quad - \left(\frac{1}{\sigma_G} - \frac{1}{\sigma_E}\right)\ln L_{ect} - \ln\phi_{egct} - \left(\frac{1}{\sigma_{M,E}} - \frac{1}{\sigma_G}\right)\ln L_{egct} \\
&\quad - \ln\beta^s_{egct} + \frac{1}{\sigma_{M,E}}\ln L_{egsct}.
\end{aligned}$$

4.2 Labor Supply

Labor supply is estimated in two steps using the technique from Berry et al. (1995, 2004). These methods have been applied to estimate workers' preferences for locations by Bayer et al. (2007) and Diamond (2016). I adapt their approach.

The indirect utility of worker i in city c in year t is given by

$$\begin{aligned}
V_{ict} &= \Gamma^z_{ct} + \lambda^{st}_{zt} st_i x^{st}_c + \lambda^d_{zt} st_i x^d_c + \lambda^n_{zt} n_i x^n_{c,t-\tau} + \varepsilon_{ict}, \\
\Gamma^z_{ct} &= \lambda^w_z\left(w^z_{ct} - \lambda^r_z r_{ct}\right) + \lambda^A_z x^A_{ct}.
\end{aligned}$$

The utility of a type z worker consists of the common utility value of the city for all workers with the same type, Γ^z_{ct} plus the network or birthplace value $\lambda^{st}_{zt} st_i x^{st}_c + \lambda^d_{zt} st_i x^d_c + \lambda^n_{zt} n_i x^n_{c,t-\tau}$, and a

[32] The KM index is computed similarly as in step 1 except that I combine hours of all types of workers.

worker-specific idiosyncratic taste for the city, ε_{ict}.

In the first step, I treat Γ_{ct}^{z} as parameters and estimate them together with the birthplace and network parameters by maximizing the log-likelihood of observed location choices. I include 114 MSAs as city choices, and combine the other MSAs as the outside option where the utility is normalized to zero. Differences in the proportions of people across cities identify the mean utilities.

In the second step, I estimate the values of each city characteristic using the mean utility from step one. Given the workers' utility function, λ_z^r represents the share of income on housing. I take the values of housing expenditure shares per household member from the combined 2005-7 ACS. I tried estimating λ_z^r jointly with λ_z^w. However, this results in a noisy estimate and unreasonable value of λ_z^r that exceeds one. Therefore, I take the values of housing expenditure shares from the data. I set λ_z^r to 0.3 for high skill natives, 0.3 for low skill natives, 0.34 for high skill immigrants and 0.36 for low skill immigrants.

The amenities x_{ct}^{A} for city c in year t consist of permanent city-specific components and time-variant components. Let ξ_{ct}^{z} denote the change in utility value of city c's time-variant amenities across decades for workers of type z. Taking first differences of the mean utilities over periods gives

$$\triangle\Gamma_{ct}^{z} = \lambda_z^w \left(\triangle w_{ct}^{z} - \lambda_z^r \triangle r_{ct}\right) + \triangle\xi_{ct}^{z}. \tag{29}$$

The change in a city's mean utility for workers of type z consists of changes in wages, rents and time-variant amenities. Note that since the mean utilities in the first step are identified relative to the outside option, changes in local prices on the RHS of (29) are defined as relative prices to the outside option. Changes in cities' local real wages: $\left(\triangle w_{ct}^{z} - \lambda_z^r \triangle r_{ct}\right)$ are observed in the data. However, amenity changes are unobserved by the researcher.

A concern with equation (29) is that $\left(\triangle w_{ct}^{z} - \lambda_z^r \triangle r_{ct}\right)$ may be influenced by unobserved changes in local amenities. Thus, I estimate λ_z^w using labor demand shocks as instrumental variables. Since the KM indices, as defined in (25), measure national changes in industrial productivity, they provide variation in local labor demand that is not related to unobserved changes in local amenities. The moment restrictions are

$$\mathrm{E}\left(\triangle\xi_{ct}^{z}\mathrm{KM}_{egct}\right) = 0. \tag{30}$$

4.3 Housing Supply

Taking first differences of cities' rents over decades, we have

$$\triangle \ln (R_{ct}) = \triangle \ln (CC_{ct}) + (\gamma^{geo} x_c^{geo} + \gamma^{regu} \ln (x_c^{regu})) \triangle \ln \left(\sum_z Z_{ct} \lambda_z^r W_{ct}^z \right).$$

I take the values of housing expenditure shares, λ_z^r from the combined 2005-7 ACS as in Section 4.2. Changes in each city's wages W_{ct}^z and population Z_{ct} as well as the measure of geographic constraints x_c^{geo} and regulatory constraints x_c^{regu} are observed in the data. However, changes in construction costs are not observed by the researcher. To identify the elasticity of housing supply, γ^{geo} and γ^{regu}, requires variation in housing demand that is not related to changes in unobserved construction costs. Define changes in unobserved construction costs as $\triangle \varepsilon_{ct}^{CC}$, the housing supply curve can be rewritten as

$$\triangle \varepsilon_{ct}^{CC} = \triangle \ln (R_{ct}) - (\gamma^{geo} x_c^{geo} + \gamma^{regu} \ln (x_c^{regu})) \triangle \ln \left(\sum_z Z_{ct} \lambda_z^r W_{ct}^z \right).$$

To instrument for changes in housing demand, I use the interactions of KM indices with housing supply elasticity determinants (Diamond, 2016). As workers migrate to arbitrage increased wages caused by the labor demand shocks, they will drive up rents. The regulatory constraint x_c^{regu} impacts the elasticity of housing supply. Cities with inelastic housing supplies exhibit larger rent increases leading to relatively less in-migration. Since the KM productivity shocks are driven by national changes in industrial productivity, the KM indices interacted with regulatory constraints provide variation in housing demand unrelated to unobserved local construction costs.[33] This leads to the following moment restrictions:

$$\mathrm{E}\left(\triangle \varepsilon_{ct}^{CC} \Theta_{ct}^z \right) = 0 \tag{31}$$

where

$$\Theta_{ct}^z \in \left\{ \mathrm{KM}_{egct}, \quad \mathrm{KM}_{egct} x_c^{regu} \right\}.$$

[33] When I include the interaction of KM indices with cities' geographic constraints x_c^{geo} as an additional instrument, the test of over-identification rejects the hypothesis that my instruments are jointly uncorrelated with unobserved local construction costs. Therefore I only include the interaction of KM indices with regulatory constraints which are partly derived from the legislative and executive actions regarding land use policies at the state level (Gyourko et al., 2008). Further, I include year fixed effects to capture any proportional changes in CC_{ct} common to all cities.

5 Baseline Results

5.1 Labor Demand

The estimates of labor demand functions are reported in Panel I of Table 1.[34] The first stage regressions and the OLS estimates are reported in Table A.5 in the Online Appendix. I estimate the elasticity of substitution between high skill natives and high skill immigrants to be 6.93, and between low skill natives and low skill immigrants to be 17.87. The estimates imply that low skill immigrants are closer substitutes to natives relative to higher skill immigrants. This could be because differences in the quality of education and English skills are less important for low skill labor. A similar conclusion is found in the city-level estimation in Card (2009). Using data at the national level, Ottaviano and Peri (2012) find that natives and immigrants have a lower substitutability among low educated workers. It is worth noting, however, that the elasticities of substitution obtained from the national approach in Ottaviano and Peri (2012), and in this paper measure different relative wage effects (see Dustmann et al. (2016a) for further discussion).

The elasticity of substitution between male and female workers, σ_G is estimated to be 1.97. Johnson and Keane (2013) estimate the elasticity of substitution between genders conditional on occupation and education to be 5.26; however, the unconditional elasticity of substitution between genders lies in the range of $1.85-2.20$. Since I do not differentiate labor types by occupation, my estimate of σ_G lies in the range of their unconditional elasticity. Finally, the elasticity of substitution between high and low skill workers is estimated to be 2.19. This parameter lies between the range of estimates at the MSA level provided by Diamond (2016) and Card (2009). For estimates at the national level, this parameter tends to be smaller (Katz and Autor, 1999). Goldin and Katz (2009) argue that the values of $1/\sigma_E$ from more recent data tend to smaller because the estimates are confounded by a slowdown in the pace of skill-biased technical change.

5.2 Worker Preferences

Panel II of Table 1 displays the elasticity of workers' demand for a city with respect to local real wage.[35] The ratio of workers' marginal utility with respect to local real wage λ_z^w to the housing expenditure share λ_z^r measures the elasticity of workers' demand with respect to local rents. The results show that all workers prefer cities with higher local real wages. High skill male natives are more sensitive to changes in local wages and rents than other groups of natives. Immigrants, except for low skill males, are much more sensitive than the native counterparts. For example, a

[34] Generalized r-squared is calculated using prediction errors from the second stage of regression as the sum of squared residuals. See Pesaran and Smith (1994) for more details.

[35] Given the distributional assumption of workers' idiosyncratic tastes for cities, the magnitudes of these coefficients represent the elasticity of workers' demand for a small city with respect to its local prices.

one percent wage rise increases the high skill male native population by about 2.1 percent, while it leads to about 3.8 percent increase in population of the immigrant counterpart. The elasticity of workers' demand with respect to local rents implies that a one percent rent increase reduces the native population by about 0.3-0.6 percent, while reducing the population of immigrants by about 0.4-1.3 percent.

Similarly, using 1980-2000 U.S. Census data, Diamond (2016) finds immigrants to be more price responsive than natives. However, her estimates for λ_z^w of immigrants are much higher than my estimates. In her model, immigrants do not value city-specific networks and they earn the same wages as natives of the same skill level. Workers also have preferences for endogenous amenities, measured by the city's college employment ratio. A higher value of λ_z^w means migration decisions are more responsive to prices, which would lead to more equalizing impacts of immigration in my counterfactuals.

Table 2 reports the estimates of birthplace and network attachments for natives and immigrants. Overall, low skill natives have stronger preferences to live in their birth states than high skill natives.[36] For example, in 2007 high skill male natives are about 2.8 times more likely to live in a given MSA if it is located in their birth states, while low skill male natives are almost 3.6 times more likely. Both low and high skill natives are less likely to live in a given MSA the farther it is from their birth states. Among high skill natives, females have slightly stronger attachments to their birthplaces than males. The reverse is true among low skill natives; however the differences are small.

The estimates in Panel II. of Table 2 show that all immigrants are more likely to live in a given MSA if it had more immigrants from the same country group in the past. This is consistent with the well-known fact that immigrants tend to settle in country-specific enclaves (Card, 2009). Overall, low skill immigrants value the size of city networks more than high skill immigrants. Amongst immigrants of the same skill level, female workers have slightly stronger preferences for networks than male workers. From 1990-2007, the values of networks are decreasing for all types of immigrants; this concurs with findings of the growing number of immigrants in nontraditional cities in the past few decades (Kritz et al., 2013).[37]

[36] This is in line with Kennan and Walker (2011) who estimate the moving cost of high school graduates to be higher than the moving cost of college workers.

[37] There are two potential drivers of this trend: (i) immigrants are becoming more mobile over time; or (ii) non-traditional areas are becoming more attractive. Existing papers find supporting evidence for both. Kritz et al. (2013) argue the higher propensity of immigrants to migrate into non-traditional areas stems from the higher mobility of professional workers. The propensity also varies by country of origin. On the other hand, Lichter and Johnson (2009) note that traditional gateway and other Hispanic areas lose domestic migrants to high growth areas.

5.3 Housing Supply

Panel III. of Table 1 shows the estimates of inverse housing supply elasticities. The estimates show that housing supply is less elastic in areas with more geographic and regulatory constraints which is consistent with Saiz (2010) and Diamond (2016). The predicted inverse housing supply elasticities, reported in Panel IV., range from 0.04 to 1.18. The average inverse housing supply elasticity is 0.68 and the standard deviation is 0.30 which are close to Saiz (2010)'s average and standard deviation.

5.4 Goodness of Fit

Mechanically, the amenities are selected to fit changes in total population over time. To assess the fit, I compare the predicted and observed numbers of sub-populations which are not directly targeted in the estimation. For natives, I compare the predicted and observed numbers of natives living outside their birthplaces. For immigrants, I compare the predicted and observed numbers of workers from major sending countries in each city. This includes Mexico, Central America, South America and the Caribbean. Figures A.1-A.3 in the Online Appendix plot the predicted and observed proportions of natives who do not live in their states of birth in 1990, 2000 and 2007, respectively. Figures A.4-A.6 show the fit of the predicted number of immigrants from the major sending countries in each year. Overall, the model predicts the proportions of each worker type across cities well.

Additionally, I use the model to replicate the wage and rent impacts of the Mariel boatlift. Card (1990) analyzes the wage impact of the arrival of Cuban immigrants in 1980 by comparing wages in Miami and comparison cities before and after the boatlift took place. He finds negligible wage effects in 1985. I use the model to examine what the long run wage impact of the Mariels would be in 1990.[38] I increased the number of Cuban immigrants in Miami by 20 percent where the gender and education composition is similar to Card (1990). This results in a 14.7 percent increase of total labor force in Miami in the fixed migration scenario. I calculate the wage impact of the increase in Miami and comparison cities: Atlanta, Houston, Los Angeles, and Tampa. After labor relocation, I find the wage impacts to be very small which is consistent with Card (1990) (see Table A.6 in the Online Appendix). Furthermore, the impact on rent is substantial only in the short run.[39] As workers relocate, the additional workers in Miami reduces to 0.93 percent. Consequently the rent increase falls from 14 percent to slightly less than one percent which concurs with Saiz (2007)'s estimate for the immigration effects on rents over decades.

[38]The estimation yields time-variant parameters for 1990, 2000 and 2007. The simulation of Mariel boatlift is based on the 1990 model parameters which, in terms of time frame, is most comparable to Card (1990)'s analysis in 1985.

[39]As documented in Saiz (2003), by 1983 the rent differential was still 7% in Miami.

Overall, this yields two implications. First, the model could replicate the effects of the Mariel boatlift on both wages and rents well. Second, there are equilibrium effects through worker relocation which translate large local shocks into small wage shocks in both treated and control cities. While the control cities are affected by the boatlift in my simulation, the equilibrium effects are small as workers relocate dispersedly.

5.5 Sensitivity Analysis

In this section, I examine the sensitivity of the estimated parameters for labor demand, labor supply and housing supply. See Table A.7 and more details in Section D of the Online Appendix. For labor demand, I check whether the estimates are sensitive to various measures of wages and labor supply as well as the ordering of the CES production function. The alternative specifications yield estimates that are close the baseline case.

For labor supply, I re-estimated the model using prices which are not expressed in relative terms, and using local good expenditure shares λ_z^r from Moretti (2013). Both of these alternative specifications yield smaller estimates of worker's value of the real wage λ_z^w. However, the Hansen-J test of over-identification rejects the hypothesis that changes in unobserved local amenities are uncorrelated with my instruments, with p-values less then 0.05 for both of these specifications.

For housing supply, I try including the interaction of geographic constraints with predetermined initial log city population in 1980.[40] Under this specification, the estimate leads to a counter-intuitive interpretation that geographic constraints matter less when population increases. Additionally, I check if the results are sensitive to a different measure of rent by using a different discount rate for rent imputation of home owners. The estimate is similar to the baseline case.

6 The Impacts of Immigration

6.1 Overview

I now analyze the effects of changes in the skill mix and stock of immigrants and evaluate three counterfactual policy experiments. The outcomes of interest are the wages, rents and welfare of different groups of workers. I measure welfare effects using changes in the indirect utility in (10).

One potential benefit that is often not included in immigration analyses is the additional rental income accruing to landlords. The U.S. Census provides information on individuals' residential house values and dividend/rental income, but the actual number of landlords who own rental property is not available. To incorporate these gains in the welfare calculation, I approximate the

[40]As noted in Saiz (2010), geographic constraints are more likely to be binding when the level of construction is high.

number of landlords by classifying workers in the combined 2005-7 ACS who meet my sample criteria and report positive rental income and positive values of houses as landlords.[41] The share of landlords consists of 71 percent high skill natives, 18.5 percent low skill natives, 8.5 percent high skill immigrants and 2 percent low skill immigrants.

In all analyses, I consider fixed and free migration cases. In the fixed migration case, the allocation of natives and immigrants across cities is held constant. In the free migration case, all workers make their location decisions simultaneously. In each counterfactual, I solve for the allocation of workers and prices using the equilibrium conditions (20)-(22). This requires finding 920 fixed points (115 city populations for 8 types of workers). I solve for the equilibrium by substituting (21) and (22) into (20) and searching for an allocation (Z^*_{ct}) such that

$$Z^*_{ct} = \underset{(Z_{ct})}{\operatorname{argmin}} \left[Z_{ct} - \Sigma_{i \in \mathscr{Z}_t} \mathrm{Pr}_{ict} \left(Z_{ct}, \Omega \right) \right]$$

where Ω is the vector of model parameters and Pr_{ict} is the choice probability in (11). The welfare analysis is based on simulated location choices of a random draw of 240,000 individuals given prices in the initial and new equilibrium.

6.2 Model Predictions

Before proceeding to the counterfactuals, let us first consider how a change in the number of immigrants affects the wages of each group. Let $d\ln L_{egmct}$ denote a hypothetical change in the number of immigrants of each type. The change in a native's wage is

$$d\ln W^n_{egct} = \frac{1}{\sigma_E}\left(d\ln L_{ct} - d\ln L_{ect}\right) + \frac{1}{\sigma_G}\left(d\ln L_{ect} - d\ln L_{egct}\right) + \frac{1}{\sigma_{M,E}} d\ln L_{egct} \tag{32}$$

Similarly, the change in an immigrant's wage is

$$\begin{aligned} d\ln W^m_{egct} = {} & \frac{1}{\sigma_E}\left(d\ln L_{ct} - d\ln L_{ect}\right) + \frac{1}{\sigma_G}\left(d\ln L_{ect} - d\ln L_{egct}\right) \\ & + \frac{1}{\sigma_{M,E}}\left(d\ln L_{egct} - d\ln L_{egmct}\right). \end{aligned} \tag{33}$$

There are three effects. First, (33) shows that increased immigration by a specific group and city will reduce the wages of immigrants by the term $-\frac{1}{\sigma_{M,E}} d\ln L_{egmct}$; the negative effect is due to decreasing marginal product of labor. However, this effect is counterbalanced by the imperfect substitutability between natives and immigrants within gender-skill groups, $\frac{1}{\sigma_{M,E}} d\ln L_{egct}$. Further, in the extreme case where immigrants and natives are perfect substitutes (i.e. $\sigma_{M,E} \to \infty$) then (32)

[41] See Section 2.1 for sample description.

and (33) become identical.

The second effect comes from the deviation in the labor supply of each gender-skill group relative to the overall supply of each skill group (which is the same for natives and immigrants): $\frac{1}{\sigma_G}\left(d\ln L_{ect} - d\ln L_{egct}\right)$. The third effect comes from changes in the aggregate supply of each skill group: $\frac{1}{\sigma_E}\left(d\ln L_{ct} - d\ln L_{ect}\right)$. Increased immigration by a specific group decreases the wages of all workers in that group. However, this effect will be mitigated by the complementarity between workers of different types.

With respect to workers' preferences, the estimates in Section 5.2 reveal that natives are 3-4 times more likely to live in a given MSA if it is located in their birth state. This implies that a city with a large share of natives who already left their birthplaces is more likely to experience an out-migration response, since this group of natives is relatively mobile. Thus the wage impacts of immigration are likely to be attenuated in these cities. Further, while immigrants value their city-specific networks (measured by the number of previous immigrants from the same country group), the availability of large networks across other cities may increase their migration propensity. For example, there are 60 cities which have more than 10,000 Mexicans (see Table A.4 for the number of cities with at least 10,000 immigrants from each country group). The fact that Mexican workers have 60 cities with large networks means that they can move across these 60 cities without losing significant network value. Therefore cities with more previous immigrants who have dispersion of large networks are more likely to have smaller wage impacts due to workers' relocation.[42]

Moreover, the estimates show that workers prefer cities with higher local real wages and amenities. Hence, cities with (i) lower productivity, (ii) more inelastic housing supply and (iii) lower amenities are more likely to experience an outflow of workers in the incidence of negative immigration shocks. Since cities have mixed characteristics, with possibly opposing effects on migration incentives, the migration response depends on the relative strength of these characteristics. Tables A.8-A.10 report the top and bottom ten cities on each of these characteristics in 2007.

6.3 Skill Selective Immigration

Some countries select immigrants based on skill. For example, Australia and Canada employ point systems which grant entry to a significantly lower proportion of unskilled workers than the U.S. (Antecol et al., 2003). In this section, I examine the price and welfare effects of an increase in immigrants if the U.S. were to adopt a skill selective immigration policy. The experiment consists of an increase in the ratio of immigrants to natives among high skill workers from 0.17 to 0.25. This figure is in line with the proportion of immigrants in the UK high skill population between 2003-2005 (Manacorda et al., 2012). This corresponds to increasing high skill immigrants by

[42] Cadena and Kovak (2016) find that natives who live in MSAs with a large number of Mexican immigrants experience a weaker relationship between local shocks and local employment probabilities.

roughly 46 percent, or around 3.6 million workers in 2007, holding the gender and origin mix constant. I consider two cases. In the first case, I increase the number of high skill immigrants in each city proportionately, holding the locations of all workers fixed. In the second case, natives and previous immigrants can migrate in response to the immigration; hence all workers, including the new immigrants, simultaneously make their location decisions.

6.3.1 National Impact

The arrival of high skill immigrants puts downward pressure on the wages of previous high skill immigrants. There is a small positive effect on the average wages of high skill natives. Table 3 reports the average annual wages of each group, expressed in 2015 dollars, weighted by employment at the city level. I present average wages for two types of city: gateway cities, defined as being in the top 5 percentile in terms of the fraction of new high skill immigrants, and all other cities. The gateway cities include Fort Lauderdale, Miami, New York, San Francisco and San Jose.

As shown in column one, the average annual wages of high skill natives in gateway cities increases by 0.2 percent for males and 0.4 percent for females (276 dollars for males and 324 dollars for females) in the fixed migration case, while the average annual wages of high skill immigrants fall by about 5 percent ($4,432$ dollars for males and $3,122$ dollars for females). The differential wage impact is due to the imperfect substitutability between high skill natives and high skill immigrants. In contrast, given the complementarity between high and low skill labor, the influx of high skill immigrants increases the wages of low skill workers. In gateway cities, the average wages of low skill labor in the fixed migration case increase by about 4 percent ($2,232$ and $1,823$ dollars for male and female natives, respectively, and $1,538$ and $1,351$ dollars for the immigrant counterparts). As shown in column five of Table 3, the average wage impacts on high skill natives and other low skill workers are much smaller in other cities since they receive fewer new immigrants.

When workers are free to move, the average gains for low skill wages become smaller. The average adverse wage impacts are slightly attenuated for high skill immigrants in gateway cities, and slightly intensified in other cities; this is displayed in columns three and seven in Table 3. It is worth noting that while these national averages in the fixed and free migration cases do not differ much, migration responses can substantially alter the distribution of the local price impacts, as will be shown in the next section.

Finally, Table 3 shows that the average annual rent weighted by city population initially increases by around 11.7 percent ($1,308$ dollars) in gateway cities, and by around 2.6 percent (224 dollars) in other cities. In the free migration case, as people move away from the popular destinations for new immigrants, the increase in rent becomes smaller relative to the fixed migration case, while rents in some smaller cities slightly rise. Overall, a one percent increase in a city's population due to immigration is associated with around a 1.24 percent increase in the average housing rent in the fixed migration case, and 1.14 percent increase in the free migration case.[43]

6.3.2 Local Impact

The top panel of Figure 1 displays the percentage change in rents when workers' locations are held fixed against the percentage change when all workers are free to migrate. Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in the associated city. Further, red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply. There is substantial variation in the rent impacts across cities. Housing rents in cities such as San Jose and Miami, where the wage gains for low skill workers are large, also have a relatively large increase in housing rents. This implies that the gains in "local real wages" of low skill workers in some places could be a lot lower than the nominal gains, and the losses in local real wages for high skill workers could be higher than the nominal losses. Further, since both changes in wages and rents impact migration decisions, I illustrate how migration responses can alter the overall distributional impact by focusing on local real wages.

I define local real wage similarly to Moretti (2013). I calculate local CPI as the weighted sum of rental cost of housing R_c and non-housing consumption, where the latter is assumed to be identical everywhere. I set the price of non-housing consumption to the average rent across cities before the influx of immigration. Further, I normalize local CPI to one for an average city in the base year. The values of housing expenditure shares are taken from the data as in Section 4.2. Figures 2-3 plot the percentage change in local real wages in the fixed against free migration cases (the scatter plots for nominal wages are available in Figures A.7-A.8 in the Online Appendix).

These scatter plots show that there is substantial variation in the impacts across cities. The initial real wage impacts are more substantial in cities with larger fractions of new high skill immigrants (represented by larger bubbles). When workers are free to move, the immigration impacts become more equalized. As can be seen in Figures 2-3, there is a mean reverting pattern of local real wages across cities. Further, there are more substantial differences in immigration impacts between the fixed and free migration cases for high skill workers. In this counterfactual policy experiment, low skill workers have less incentive to move since the gains in their wages partially offset the increased housing cost.

The local real wages of high skill workers tend to improve in cities with inelastic housing supply as high skill workers out-migrate to more affordable cities. For instance, the local real

[43] This is obtained by regressing the changes in rents on changes in local population in the counterfactual. This result is in line with Saiz (2007) who finds a one percent increase of a city's population due to immigration is associated with a one percent increase in average housing rents and prices.

wage of high skill male natives in Miami decreases by 6.7 percent in the fixed migration case, but after workers relocate, about half of this adverse effect attenuates. An out-migration response of high skill workers decreases housing rents, benefitting other stayers in Miami. However, the overall benefit associated with internal migration on local real wages can be smaller for low skill workers. This is because an out-migration of workers of a given type raises the local wages for all workers of that type, while reducing the local wages of workers with complementary characteristics. Given the complementarity between high and low skill labor, the nominal wages of low skill workers fall as high skill workers leave the city.

As discussed in the previous section, the model predicts that a city with undesirable characteristics (more inelastic housing supply, lower productivity and lower amenities), would have a larger outflow of incumbent workers in response to immigration, all else equal. Second, a city with a higher share of natives who have already left their birthplaces and immigrants with dispersion of large networks should experience a stronger out-migration response. This is because these workers are relatively mobile and so more likely to migrate in response to the immigration (see Tables A.8-A.10 for the list of top and bottom cities ranked by each characteristic). Therefore, a city with relatively elastic housing supply may have more out-migration if it also has more mobile workers. One example is Atlanta, GA which has an inverse housing supply elasticity of 0.47 but experiences a larger fraction of high skill male natives (3 percent) moving out in response to immigration than Santa Barbara, CA (0.7 percent) which has an inverse housing supply elasticity of 1.38. The main difference between these two cities is that 48 percent of workers in Atlanta are natives who have left their birth states, while this figure is only 24 percent in Santa Barbara. While housing supply elasticities and location attachments are important, other factors such as amenities and city-specific productivity also affect location choices. For example, the amenity value in Augusta-Aiken, GA-SC is ranked in the bottom 25 percentile for high skill female natives. Although the initial wage and rent impacts are negligible the relatively low amenity level causes a relatively high level of out-migration. In the next section, I summarize how the interaction between city characteristics and migration responses may impact the distribution of welfare.

6.3.3 Welfare Analysis

In this section, I summarize the welfare effects using changes in the indirect utility. The welfare analysis is based on simulated outcomes among a random draw of 240,000 individuals. First, I show that a wage analysis alone does not provide an informative representation of the welfare impact distribution. This is true even when immigration leads to qualitatively similar average effects on both rents and wages because the two price distributions can differ and workers could respond to each price change differently. Second, even after adjusting wages for rent changes, an analysis based on local real wages does not completely capture the welfare distribution.[44] I measure welfare effects as changes in the indirect utility taking into account the impacts on wages, housing rents and workers' utility derived from city specific amenities and networks. I illustrate these points by regressing changes in average welfare in the free migration case on (i) changes in wages and (ii) changes in local real wages under fixed migration. Let $\triangle u_{ct}^{z*}$ denote the percentage change in average welfare of workers' type z in the free migration case where welfare is expressed in wage units. For a given type-z worker,

$$\triangle u_{ct}^{z*} = \beta_0^w + \beta_1^w \triangle \ln W_{ct}^z + \varepsilon \tag{34}$$

$$\triangle u_{ct}^{z*} = \beta_0^{lrw} + \beta_1^{lrw} \triangle \ln W_{ct}^z / P_c + \varepsilon \tag{35}$$

where $\triangle \ln W_{ct}^z$ is the percentage change in wage in the fixed migration case and $\triangle \ln W_{ct}^z / P_c$ is the percentage change in local real wage in the fixed migration case.

The first two columns of Table 4 report β_1^w and the values of R-squared for estimates of (34). The low values of R-squared indicate that the variation in changes in wages do not represent changes in overall welfare well. This is because rents also change considerably. The last two columns report β_1^{lrw} and the values of R-squared for (35) when wages are adjusted for changes in rents. If there is little spatial equilibrium effect in the sense that heterogeneity in workers' preferences and migration responses are not important, then local real wages in the fixed migration should capture the equilibrium distribution of welfare changes. While there is generally an increase in the R-squared for (35) relative to (34), variation in local real wages explains less than half of variation in the equilibrium welfare effects for some types of workers. Further, the fact that β_1^{lrw} is estimated to be less than one implies that changes in local real wages tend to overstate the true changes in welfare implied by a spatial equilibrium model.

For the above reasons, I summarize the welfare effects using changes in the indirect utility. Table 5 reports changes in average welfare in annual wage units by worker type in gateway and other cities. In the fixed migration case, the average welfare impact on high skill natives in gateway cities is equivalent to a reduction of almost 3 percent in annual consumption ($3,034$ and $2,114$ dollars for males and females, respectively). The reduction is considerably more severe for high skill immigrants, equivalent to around a 8 percent loss in annual consumption ($7,497$ and $5,344$ dollars for males and females). The impacts are less substantial in other cities. Among low skill workers in gateway cities, average welfare improves by around 1 percent for natives (569 and 463 dollars for male and female natives), and by 0.4 percent for the immigrant counterparts (146 and 116 dollars for male and female immigrants); the average gains for low skill workers in other cities are similar to those in gateway cities.

[44] I define local real wage similar to Moretti (2013). See Section 6.3.2 for more details.

In the free migration case the negative impacts on the average welfare of high skill natives and high skill immigrants in gateway cities attenuate. The welfare losses of those who move from gateway cities are substantially mitigated. This is shown in columns 5 and 7 of Table 5, where the change in utility of "forced stayers" measures the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move. The difference between the change in welfare of movers and forced stayers represent the "gains from internal migration", equivalent to an almost $1,000$ dollar increase in annual consumption for high skill natives in gateway cities. The welfare gains for low skill natives become slightly smaller. Further, none of the simulated low skill male natives move from gateway cities. This is because low skill male natives are more attached to places than other groups. Additionally, their wage gains compensate the increased housing rents and so they have little incentive to migrate.[45]

To illustrate local variation, Figures 4 and 5 show maps of quartiles of the percentage change in average welfare of each skill-nativity group from the initial levels to the free migration levels. Internal migration responses reduce the initial wage and rent impact in more adversely affected cities. However, even after worker relocation, the welfare impact of immigration is unevenly distributed across and within cities. The biggest winners among native workers in this case are low skill labor in Houston, TX (1.6 percent increase in local real wage), while the biggest losers are high skill labor in Miami, FL (3.3 percent decline in local real wage). Similarly high skill immigrants in Miami, FL lose the most, (8.6 percent decline in average welfare), while low skill immigrants in Houston, TX gain more than all other workers (1.5 percent increase in local real wage).

Further, I summarize the welfare effects by types of cities by regressing the percentage change in average welfare of workers' type z in the free migration case $\triangle u_{ct}^{z*}$ on city characteristics. These characteristics include the city's housing supply elasticity, city-specific productivity, type-specific values for local amenities, the share of natives who already left their birthplaces, and the share of immigrants with a large network.[46] The results in Table (6) show that workers in cities with more inelastic housing supply are hurt by this policy. High skill workers in cities with high amenities and high productivity are worse off, and high skill workers are better off. The attractiveness of high amenities and high productivity in these places draws high skill workers from cities that are more affected by immigration. Given complementarity between high and low skill labor this leads

[45] The welfare benefits from this counterfactual policy could be larger if, for example, there are positive externalities from high skill workers (Moretti, 2004b; Diamond, 2016). Further, immigration may enhance welfare through other channels of adjustment such as growing exports of tourism service (Tadesse and White, 2012) and increased ethnic diversity of restaurants (Mazzolari and Neumark, 2012).

[46] I define a network of immigrants to be large if there are at least 20 cities with at least 10,000 immigrants from the same country group. These large network immigrants include those from Mexico, Central and South America, Central Europe, Canada and other North American countries.

to higher wages for low skill workers, compensating them for welfare losses from rising housing costs. The variation in productivity, however, appears to be less important than the variation in amenities in determining the spatial distribution of welfare consequences from immigration. Moreover, high (low) skill workers in cities with higher shares of immigrants with large networks experience greater reduction (increase) in welfare since these cities experience larger inflows of new immigrants. Finally, while the effects of variation in the number of mobile natives who already left their birthplaces are not statistically significant for all groups, the results show that incumbent high skill male natives and immigrants in cities with a higher share of mobile natives are insured against the adverse effects of skill selective immigration policy.

One potential benefit that is usually not included in immigration studies is the increased housing rents accruing to landlords. This additional income can be significant, but not necessarily evenly distributed. In the last panel of Table 5, I show welfare changes with the additional rental income distributed based on the share of landlords in 2007: 71 percent high skill natives, 18.5 percent low skill natives, 8.5 percent high skill immigrants and 2 percent low skill immigrants. The increased rental income per landlord is $1,251$ dollars for high skill natives, 367 dollars for low skill natives, 874 for high skill immigrants and 154 dollars for low skill immigrants. With the additional rental income, high skill immigrants are the only group who lose. The average net welfare gain after worker relocation is 94 dollars per person.

Overall, a policy favoring the entry of high skill immigrants improves the welfare of all workers, except for the high skill immigrants themselves. There is a substantial increase in welfare of high skill native landlords, more than compensating for their initial losses. Further, this policy leads to reduced real wage inequality. As shown in the lower panel of Table 3, the 90-50 and 90-10 local real wage ratios, across workers of different groups and cities, decline as a result of having more high skill immigrants.

6.4 Change in the Stock of Immigrants

To better understand how the skill composition of immigrants leads to different distributional consequences, I increase the stock of immigrants in this experiment by the same magnitude as in the previous counterfactual, but hold the skill and gender mix constant as in 2007. This corresponds to roughly a 25 percent increase in the stock of immigrants in 2007, or 1.5 million new high skill immigrants and 2.1 million new low skill immigrants.

6.4.1 National Impact

The changes in average wages are reported in Table 7. The annual wage, expressed in year 2015 dollars, of each group is weighted by employment at the city level. The gateway cities (defined as those in the top 5 percentile in terms of attracting new immigrants in the counterfactual) include Los Angeles, Miami, New York, Salinas-Sea and San Jose. In this counterfactual, a larger portion of the new immigrants are low skill. Given the complementarity between high and low skill labor, the average wages of high skill natives in gateway cities rise by 1.2 percent ($1,285$ dollars for males and 944 dollars for females), more than double of the wage increase in the first counterfactual. The effects are smaller in other cities. The average wages of high skill immigrants fall by slightly more than 1 percent ($1,142$ dollars for males and 792 dollars for females). The losses are about 4 times smaller than the reduction in the previous counterfactual.

The reduction in the average wages of low skill natives in gateway cities are small, less than 1 percent (224 dollars for males and 26 dollars for females). The effect is even slightly positive on the average wages of low skill female natives in other cities, an increase of 0.1 percent (47 dollars). In contrast, the average wages of low skill immigrants fall by 1.4 percent for males (476 dollars) and 1 percent for females (299 dollars). The differential wage impacts between immigrants and natives are due to their imperfect substitutability. The negative wage impacts are more concentrated on immigrants.

6.4.2 Local Impact

The lower panel of Figure 1 displays the distribution of the percentage change in rents across cities. Rents rise in all cities due to the increased population. A one percent increase in the immigrant population is associated with a 0.89 and 0.84 percent increase in the average housing rent in the fixed and free migration cases respectively. Overall, the effect of immigration on housing rents is smaller than in the first counterfactual. This is because an inflow of high skill workers puts more upward pressure on housing demand than low skill workers, and a larger portion of the new immigrants in this counterfactual are low skill.

Figure 6 plots the percentage change in natives' local real wages when the workers' locations are held fixed against the percentage change when all workers are free to migrate.[47] Each bubble is a metropolitan area. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply. Figure 7 displays the same comparison for immigrants' local real wages across cities (see Figures A.9-A.10 in the Online Appendix for scatter plots of nominal wages). Figures 6-7 show a mean reversion of immigration impacts. As workers relocate, the negative impacts on local real wages are generally more attenuated in cities that are initially more affected. Relative to the first counterfactual, low skill workers are more adversely impacted and hence exhibit more migration responses. The negative impact on local real wages of high skill workers are much smaller than in the first counterfactual. This is because a

[47] I define local real wage similar to Moretti (2013). See Section 6.3.2 for more details.

larger portion of new immigrants are low skill and so the negative wage effect is counterbalanced by the complementarity between high and low skill labor.

As discussed earlier, cities are more likely to experience out-migration of workers in response to adverse local shocks if they have either (i) higher shares of workers who are less attached to their current locations or (ii) undesirable characteristics such as inelastic housing supply, low amenities and low city-specific productivity (see Section 6.2 for more discussion). The out-migration response is particularly strong in Miami as can be seen in the lower panels of Figures 6 and 7. This is consistent with the model predictions given that Miami has a lot of previous immigrants who are more mobile (even after excluding Cubans who have relatively little dispersion of large networks) and more sensitive to price changes. Additionally, Miami is one of top 10 cities with most inelastic housing supply.

In summary, relative to the first counterfactual, the increase in the stock of immigrants has a less adverse impact on the local real wages of high skill workers. However, the local real wages of both low skill natives and low skill immigrants fall in most cities. In terms of spatial inequality, the increase in the stock of immigrants lead to slightly bigger differences between the local real wages of the very top and bottom workers (see Table 7).

6.4.3 Welfare Analysis

Table 8 reports β_1^w, β_1^{lrw} and the corresponding R-squared for (34) and (35) when the stock of immigrants increases. Relative to the first counterfactual, the spatial equilibrium effects are less strong in this counterfactual. Both changes in wages and changes in local real wages can explain a greater proportion of the variation in changes in welfare as reflected in the higher values of R-squared. This is because the changes in wages and rents, and hence migration responses, are less substantial in this experiment. Nevertheless, the values of R-squared are less than 50 percent for some groups of workers.

Table 9 reports changes in the average welfare of each group in gateway and other cities, where welfare is measured by the average utility expressed in annual wage units. In comparison with the first counterfactual, all groups experience welfare losses in this case; however the average welfare losses of high skill workers are about $2-4$ times smaller than the losses in the first counterfactual. In gateway cities, the losses of high skill natives are equivalent to a reduction of about 1 percent in annual consumption (996 dollars for males and 625 dollars for females) in the fixed migration case. The losses are larger for high skill immigrants, a reduction of almost 4 percent ($3,140$ dollars and $2,257$ dollars for males and females, respectively). The welfare losses among low skill natives in gateway cities are about 2 percent ($1,228$ dollars for males and 867 dollars for females) and the average losses are almost 4 percent for low skill immigrants ($1,282$ dollars for males and 1,038 for females). The losses for low skill labor are much smaller in other cities. When workers are free to move, the losses are mitigated for all groups in gateway cities, but become slightly larger for some groups in other cities. Overall, the gains from migration as measured by the difference between the change in welfare of movers and forced stayers are larger for low skill workers in this experiment relative to the first experiment as they are much more adversely affected in this policy counterfactual.[48]

To illustrate the local variation of welfare effects, Figures 8 and 9 maps quartiles of the percentage change in average indirect utility of each skill-nativity group from the initial levels to the free migration levels. The biggest winners among natives are high skill labor in Lubbock, TX (0.5 percent increase in local real wage), while the biggest losers are low skill labor in Santa Barbara, CA (2.5 percent decline in local real wage). Among immigrants, the biggest losers are high skill workers in Miami, FL (4.2 percent decline in local real wage), but the loss is less than half of the reduction under a skill selective immigration policy. In terms of spatial inequality, the increase in the stock of immigrants leads to slightly bigger differences between the local real wages of the very top and bottom income earners (see Table 7).

Table (10) reports how changes in the average welfare of workers of type z in the free migration vary by city characteristics. In this counterfactual where a larger portion of new immigrants are low skill, variation in the share of mobile natives (who tend to be high skill) and amenities appear not to be important factors in determining the spatial distribution of welfare impacts from immigration. There is no statistically significant effect of variation in the share of immigrants with large networks on changes in the welfare of high skill natives and immigrants. However, low skill workers in cities with more immigrants with large networks experience a greater reduction in welfare. Overall, both high and low skill incumbent workers in cities with more inelastic housing supply and higher productivity experience greater reduction in welfare as they face a larger increase in housing costs and a larger inflow of workers from other cities.

Finally, the increased rental income per landlord becomes slightly lower in the free than in the fixed migration scenario. This additional income is 884 dollars for high skill natives, 259 dollars for low skill natives, 618 dollars for high skill immigrants, and 109 dollars for low skill immigrants. While the total additional rental income gains in this case are smaller relative to the first counterfactual, the average welfare gains when rental income is redistributed are slightly larger than the first counterfactual, an equivalent of an increase in annual consumption of 98 dollars per person.[49] This is primarily because the welfare losses for high skill workers are much smaller.

[48]The change in utility of forced stayers is the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move.

[49]The rental income redistribution is based on the share of landlords in 2007: 71 percent high skill natives, 18.5 percent low skill natives, 8.5 percent high skill immigrants and 2 percent low skill immigrants.

6.5 The US-Mexico Wall

President Donald Trump has made a promise to build a border wall between the US and Mexico since his election campaign (Crilly, 2018). The President demands a budget of \$5 billion for construction of the wall (Litvan and Wasson, 2018). This calls into question whether the benefits of the wall would outweigh the cost. While the effects of the wall on the stock of immigrants is ambiguous, it is plausible that the wall would reduce the inflow of illegal immigrants entering from the border.[50] Therefore, in this counterfactual, I simulate the effects of the wall by reducing the inflow of illegal immigrants.

I do not observe legal status of immigrants in the data. However, Passel (2005) estimates an average annual inflow of undocumented immigrants of 500,000, with 57 percent of these individuals coming from Mexico. Borjas (2017) estimates the skill composition of undocumented immigrants to be 33.6 percent high skill and 66.4 percent low skill, and 56 percent male and 44 percent female. Using the gender-skill composition from Borjas (2017) and the estimated inflow of undocumented immigrants from Mexico from Passel (2005), I simulate the effects of the wall on prices and welfare under several cases by removing 20, 50 and 80 percent of the inflow of potentially illegal immigrants from Mexico in the adjacent states.[51] These states include California, Texas, Arizona and New Mexico. Note that the Department of Homeland Security estimates that the number of migrants potentially affected by the border wall to be 170,000 for the financial year 2015 (Crilly, 2018). Additionally, using a location choice model Allen et al. (2019) estimate that the wall would reduce the migration flow by 129,000 persons. These figures lie between the second and third cases where I remove 50 and 80 percent of the inflow of potentially illegal immigrants, as shown in Table 11.

One consequence of the additional number of immigrants is that housing rents in some areas would increase, at least in the short run. However, the long run impacts on the wages and welfare of different groups of workers and whether the benefits would outweigh the cost are less clear. Table 12 reports the changes in wages and rents in the baseline case where there is no reduction in the inflow of illegal immigrants, and in cases where I remove 20, 50 and 80 percent of the inflow. For comparison purposes, all changes are relative to the case of no additional illegal immigrants. Rents increase less when the inflow of undocumented immigrants reduces. In the long run, as the increased rents induce people to migrate out of these cities, rents revert towards the initial levels. This leads to a negligible effect even when there is no reduction in the inflow of potentially illegal immigrants. Meanwhile, given that 66 percent of the additional immigrants are low skill, this

[50] The effects of the wall on the stock of immigrants is unclear since undocumented immigrants who have already entered the U.S. may try to stay longer, or some repeated migrants may decide not to return to their country given the higher entry cost (Angelucci, 2012; Lessem, 2018).

[51] While modeling location decisions of illegal immigrants is interesting, it is beyond the scope of the paper. See Lessem (2018) and Allen et al. (2019) for a model of Mexican immigrants' location choices.

causes the wages of high skill workers in those cities to rise. As we reduce the inflow of these immigrants, the gains become smaller. At the same time, the negative impact on the wages of low skill workers are attenuated. Table 13 summarizes changes in welfare.

Overall, the effects on wages, rent and welfare are small for workers in the four states adjacent to Mexico as well as in other cities. Given the number of workers, the proposed construction cost is about 47 dollars per worker. Table 13 shows that the average welfare effects are positive when additional rental income are taken into account. Without rental income, the average losses, under a range of scenarios, are equivalent to a decrease in annual consumption of 5 – 24 dollars per person. Even when 80 percent of the inflow is removed, the reduction in the average losses per worker relative to the baseline would still be smaller than the estimated construction cost. These results show that the potential benefits of the border wall are considerably lower than the estimated construction cost.

6.6 Sensitivity of Counterfactual Analyses

In this section, I examine the sensitivity of counterfactual analyses using (i) the estimates of labor demand at the national level from Ottaviano and Peri (2012), (ii) the labor demand estimates when I reverse the order of gender and skill in the production function, and (iii) the estimates of workers' marginal utility with respect to local real wage from Diamond (2016).

The results from (i) are quite different. This is not surprising since Ottaviano and Peri (2012)'s estimates of the substitutability between natives and immigrants are substantially different from my estimates. The national average welfare change in this case is similar to my base line case. However, given that all other parts of the model are estimated at the city level and given that the estimates from OP and my paper measure different objects, it is more consistent to compute the immigration impacts using my own labor demand estimates. The results from (ii) and (iii) are qualitatively similar to the baseline case with some small differences quantitatively. See Section E in the Online Appendix for more discussion and tables of results.

7 Conclusion

The effects of immigration are the subject of considerable debate in the U.S. This paper quantifies the impact of immigration in a spatial equilibrium model, taking into account migration responses as well as heterogeneity in labor types and city characteristics. Despite the public concern, the results indicate that a large increase in the stock of immigrants has little impact on the wages of natives. The impacts are more highly concentrated on previous immigrants. Most welfare losses come from rising housing costs.

Further, a policy favoring the entry of high-skill immigrants leads to welfare gains for low skill workers, while reducing the wages and welfare of high skill workers. As a result, this policy reduces local real wage inequality across workers. The gains from internal migration are sizable, particularly for high skill natives in the popular destinations of immigrants. Finally, an assessment of the welfare effects from a border wall between the U.S. and Mexico shows that the potential benefits are substantially smaller than the proposed construction cost.

Overall, this paper shows that there are substantial variations in the welfare effects of immigration across and within local labor markets. An analysis based on wages or local real wages alone does not give a full representation of the welfare distribution. Out-migration in response to new migrants tends to be stronger in cities with larger shares of previous immigrants and natives who already left their birthplaces. Cities with (i) lower productivity, (ii) more inelastic housing supply or (iii) lower amenities are also more likely to have an outflow of incumbent workers. The effects of city amenities, however, are less important determinants of the spatial distribution of welfare consequences when a larger portion of new immigrants are low skill. Overall, internal migration leads to a more equalizing immigration impact across locations. Further, it is important to take into account heterogeneity in labor types: an out-migration of workers of a given type raises the local wages for workers of that type, while reducing the local wages of workers with complementary characteristics. In all cases, there is a significant increase in rental income accruing to landlords from increased immigration. This suggests that an appropriate tax scheme on rental income and housing regulations would be an important consideration if policymakers want to redistribute gains/losses more evenly.

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Table 1: Parameter Estimates

I. Labor Demand				
	skill level	gender	high-skill nativity	low-skill nativity
Elasticity of Sub.	2.193**	1.973**	6.925**	17.870**
	(0.109)	(0.167)	(0.154)	(0.819)
Generalized R^2	0.638	0.388	0.448	0.462

II. Worker preferences				
	High skill male natives	High skill female natives	Low skill male natives	Low skill female natives
Wage	2.086**	1.018**	1.323**	1.725**
	(0.253)	(0.801)	(0.071)	(0.064)
Implied Rent	-0.626	-0.305	-0.397	-0.518
	High skill male immigrants	High skill female immigrants	Low skill male immigrants	Low skill female immigrants
Wage	3.839**	3.825**	1.228**	2.964**
	(0.408)	(0.218)	(0.131)	(0.188)
Implied Rent	-1.305	-1.301	-0.442	-1.067
Hansen's J p-value	0.070			

III. Housing Supply Elasticities		
	Geo	Regulation
	0.909**	0.526**
	(0.121)	(0.040)
Hansen's J p-value	0.207	

IV. Predicted Inverse Housing Supply Elasticities			
Mean	0.683	Minimum	0.039
SD	0.303	Maximum	1.183

Standard errors in parentheses, computed using 100 bootstrapped samples. **p<0.05, *p<0.1. Generalized r-squared calculated using prediction errors. Wage parameter estimates represent worker's demand elasticity with respect to local real wage in a small city. Implied rent preferences computed using the housing expenditure shares multiplied by worker's demand elasticity with respect to local real wage. See text for more details.

Table 2: Network Effects for Natives and Immigrants

I. Natives						
	1990	2000	2007	1990	2000	2007
	High skill male natives			High skill female natives		
Birth state	2.73**	2.737**	2.78**	2.793**	2.846**	2.907**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.007)
Distance (1000 miles)	-0.684**	-0.638**	-0.638**	-0.716**	-0.667**	-0.662**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
	Low skill male natives			Low skill female natives		
Birth state	3.525**	3.59**	3.63**	3.405**	3.498**	3.572**
	(0.007)	(0.006)	(0.009)	(0.007)	(0.008)	(0.01)
Distance (1000 miles)	-0.649**	-0.583**	-0.578**	-0.745**	-0.662**	-0.631**
	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.01)

II. Immigrants						
	1990	2000	2007	1990	2000	2007
	High skill male immigrants			High skill female immigrants		
Number of previous	2.245**	1.443**	1.034**	2.442**	1.721**	1.2**
immigrants (in million)	(0.027)	(0.014)	(0.013)	(0.038)	(0.018)	(0.017)
	Low skill male immigrants			Low skill female immigrants		
	1990	2000	2007	1990	2000	2007
Number of previous	2.767**	1.718**	1.286**	2.844**	1.818**	1.377**
immigrants (in million)	(0.02)	(0.019)	(0.022)	(0.023)	(0.017)	(0.018)

Standard errors in parentheses, computed using 100 bootstrapped samples. **p<0.05, *p<0.1.

Table 3: Changes in Annual Wages: Increase in High Skill Immigrants

	Gateway cities				Other cities			
	△ annual wage Fixed migration		△ annual wage Free migration		△ annual wage Fixed migration		△ annual wage Free migration	
	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
High-skill male native	276	0.2	392	0.3	-55	-0.1	-62	-0.1
High-skill female native	324	0.4	413	0.5	68	0.1	63	0.1
Low-skill male native	2,232	4.3	1,928	3.7	543	1.2	583	1.4
Low-skill female native	1,823	4.3	1,571	3.7	443	1.3	473	1.4
High-skill male immigrant	-4,432	-5.1	-4,084	-4.7	-4,046	-5.4	-4,146	-5.5
High-skill female immigrant	-3,122	-4.9	-2,930	-4.6	-2,897	-5.2	-2,983	-5.3
Low-skill male immigrant	1,538	4.4	1,311	3.8	652	2.1	643	2.0
Low-skill female immigrant	1,351	4.5	1,155	3.8	557	2.1	543	2.0
Housing rents	1,308	11.7	1,095	9.8	224	2.6	226	2.6

	90-50 local real wage ratio	90-10 local real wage ratio
Initial	1.65	2.56
Fixed migration	1.62	2.49
Free migration	1.63	2.50

Gateway cities: Fort Lauderdale, Miami, New York, San Francisco and San Jose. Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. Fixed-migration change measures the difference between the initial wages and the wages when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table 4: Spatial Equilibrium Effects: Increase in High Skill Immigrants

Dependent variation: $\triangle$% welfare in free migration				
Independent variable:	$\triangle$% wage		$\triangle$% local real wage	
	Fixed migration		Fixed migration	
	β_1^w	R^2	β_1^{lrw}	R^2
	[1]	[2]	[3]	[4]
High-skill male native	-1.34**	0.15	0.39**	0.86
High-skill female native	-0.71**	0.04	0.54**	0.87
Low-skill male native	-0.04**	0.01	0.37**	0.27
Low-skill female native	-0.01**	0.00	0.25**	0.31
High-skill male immigrant	-1.15**	0.11	0.32**	0.68
High-skill female immigrant	-0.75**	0.05	0.42**	0.78
Low-skill male immigrant	-0.16**	0.19	0.39**	0.53
Low-skill female immigrant	-0.12**	0.21	0.29**	0.58

The average change in welfare is the percentage change in average indirect utility, expressed in dollars. The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Each regression is weighted by city employment. ** and * signify p-value <0.05 and p-value <0.1, respectively, for the Wald test whether changes in wages in the fixed migration perfectly line up with changes in the variable of interest, i.e. whether $\beta_1 = 1$. The test of whether $\beta_1 = 0$ yields similar p-values.

Table 5: Welfare: Increase in High Skill Immigrants

	△ ave. utility									
	Fixed migration		Free migration							
	all workers		all workers		movers		forced stayers		stayers	
	△$	△%	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gateway cities:										
High-skill male native	-3,304	-2.9	-2,696	-2.3	-1,785	-1.5	-2,750	-2.4	-2,716	-2.4
High-skill female native	-2,114	-2.7	-1,691	-2.2	-1,093	-1.5	-1,891	-2.6	-1,700	-2.2
Low-skill male native	569	1.1	493	0.9	.	.	.	.	493	0.9
Low-skill female native	463	1.1	395	0.9	270	0.7	163	0.4	395	0.9
High-skill male immigrant	-7,497	-8.6	-6,711	-7.7	-6,235	-7.2	-6,813	-7.9	-6,730	-7.7
High-skill female immigrant	-5,344	-8.4	-4,817	-7.6	-4,399	-7.0	-4,873	-7.8	-4,836	-7.6
Low-skill male immigrant	146	0.4	139	0.4	141	0.4	-54	-0.2	139	0.4
Low-skill female immigrant	116	0.4	118	0.4	91	0.3	-9	0.0	118	0.4
Other cities:										
High-skill male native	-831	-0.9	-787	-0.9	-1,030	-1.1	-1,476	-1.6	-786	-0.9
High-skill female native	-435	-0.7	-451	-0.7	-582	-0.9	-989	-1.5	-450	-0.7
Low-skill male native	347	0.8	351	0.8	369	0.9	238	0.6	351	0.8
Low-skill female native	288	0.8	289	0.8	266	0.8	174	0.5	289	0.8
High-skill male immigrant	-4,855	-6.5	-4,964	-6.7	-5,237	-7.0	-5,609	-7.5	-4,962	-6.6
High-skill female immigrant	-3,520	-6.3	-3,622	-6.5	-4,029	-6.9	-4,402	-7.6	-3,616	-6.5
Low-skill male immigrant	176	0.6	188	0.6	240	0.8	129	0.4	188	0.6
Low-skill female immigrant	144	0.5	152	0.6	171	0.6	110	0.4	152	0.6
Ave. loss/gains without rental income	-723	-0.8	-686	-0.8	-2,385	-3.1	-2,826	-3.7	-677	-0.8
Welfare with rental income										
High-skill native	452	2.4	509	2.4	223	2.0	-342	1.3	511	2.4
Low-skill native	703	4.0	701	4.0	684	3.9	574	3.6	701	4.0
High-skill immigrant	-4,057	-5.9	-3932	-5.8	-4175	-5.9	-4640	-6.6	-3,927	-5.8
Low-skill immigrant	314	3.6	322	3.6	326	3.2	216	2.9	322	3.6
Ave. loss/gains with rental income	57	2.2	94	2.2	-1458	-0.8	-1900	-1.4	103	2.3

The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Changes in average utility reported in 2015 annual wage dollars. Forced stayer's change in utility measures the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move. Net loss/gains weighted by population share of each group. See text for more details.

Table 6: City Characterization: Increase in High Skill Immigrants

Dependent variation: △% welfare in free migration						
Independent variable:	Housing supply	Local productivity	Local amenity	Share of mobile natives	Share of mobile immigrants	R^2
	[1]	[2]	[3]	[4]	[5]	[6]
High-skill male native	-0.67**	-0.21**	-0.15**	0.23**	-0.38**	0.79
High-skill female native	-0.75**	-0.12**	-0.17**	0.08	-0.34**	0.76
Low-skill male native	-0.55**	-0.00	0.44**	-0.10	0.37**	0.32
Low-skill female native	-0.85**	0.35**	0.21**	0.07	0.38**	0.51
High-skill male immigrant	-0.34**	-0.19**	-0.16*	0.17*	-0.28**	0.46
High-skill female immigrant	-0.57**	-0.09	-0.31**	0.09	-0.19**	0.70
Low-skill male immigrant	-0.78**	-0.12	0.36**	0.03	0.08	0.45
Low-skill female immigrant	-0.95**	0.14**	0.17**	0.15**	0.16*	0.63

Each regression is weighted by city employment and all variables are standardized. ** and * signify p-value <0.05 and p-value <0.1, respectively.

Table 7: Wages: Increase in the Stock of Immigrants

	Gateway cities				Other cities			
	△ annual wage Fixed migration		△ annual wage Free migration		△ annual wage Fixed migration		△ annual wage Free migration	
	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
High-skill male native	1,285	1.2	1,187	1.1	291	0.3	297	0.4
High-skill female native	944	1.2	823	1.1	246	0.4	256	0.4
Low-skill male native	-224	-0.4	-226	-0.5	-44	-0.1	-39	-0.1
Low-skill female native	-26	-0.1	181	0.4	47	0.1	36	0.1
High-skill male immigrant	-1,142	-1.4	-1,138	-1.4	-1,554	-2.0	-1,617	-2.1
High-skill female immigrant	-792	-1.3	-844	-1.4	-1,092	-1.9	-1,145	-2.0
Low-skill male immigrant	-476	-1.4	-470	-1.4	-409	-1.3	-392	-1.2
Low-skill female immigrant	-299	-1.0	-137	-0.5	-242	-0.9	-251	-0.9
Housing rents	779	7.5	674	6.4	156	1.8	153	1.8

	90-50 local real wage ratio	90-10 local real wage ratio
Initial	1.65	2.56
Fixed migration	1.67	2.59
Free migration	1.67	2.59

Gateway cities: Los Angeles, Miami, New York, Salinas-Sea and San Jose. Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. Fixed-migration change measures the difference between the initial wages and the wages when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table 8: Spatial Equilibrium Effects: Increase in Stock of Immigrants

Dependent variation: $\triangle$% welfare in free migration				
Independent variable:	$\triangle$% wage		$\triangle$% local real wage	
	Fixed migration		Fixed migration	
	β_1^w	R^2	β_1^{lrw}	R^2
	[1]	[2]	[3]	[4]
High-skill male native	-0.53**	0.29	0.40**	0.67
High-skill female native	-0.70**	0.34	0.53**	0.91
Low-skill male native	0.92**	0.19	0.67**	0.89
Low-skill female native	1.16**	0.38	0.30**	0.36
High-skill male immigrant	-0.46**	0.15	0.32**	0.39
High-skill female immigrant	-0.68**	0.36	0.41**	0.83
Low-skill male immigrant	0.97**	0.18	0.64**	0.93
Low-skill female immigrant	1.07**	0.32	0.37**	0.73

The average change in welfare is the percentage change in average indirect utility, expressed in dollars. The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Each regression is weighted by city employment. ** and * signify p-value <0.05 and p-value <0.1, respectively, for the Wald test whether changes in wages in the fixed migration perfectly line up with changes in the variable of interest, i.e. whether $\beta_1 = 1$. The test of whether $\beta_1 = 0$ yields similar p-values.

Table 9: Welfare: Increase in the Stock of Immigrants

	△ ave. utility									
	Fixed migration		Free migration							
	all workers		all workers		movers		forced stayers		stayers	
	△$	△%	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gateway cities:										
High-skill male native	-996	-0.9	-834	-0.8	-554	-0.5	-948	-0.9	-837	-0.8
High-skill female native	-625	-0.8	-562	-0.7	-341	-0.5	-633	-0.9	-564	-0.8
Low-skill male native	-1,228	-2.4	-1,114	-2.2	-736	-1.5	-1,164	-2.4	-1,122	-2.2
Low-skill female native	-867	-2.1	-565	-1.3	-384	-0.9	-653	-1.5	-567	-1.3
High-skill male immigrant	-3,140	-3.8	-2,874	-3.4	-2,605	-3.2	-2,904	-3.6	-2,879	-3.4
High-skill female immigrant	-2,257	-3.7	-2,115	-3.4	-1,898	-3.2	-2,107	-3.5	-2,120	-3.4
Low-skill male immigrant	-1,282	-3.8	-1,185	-3.5	-919	-2.7	-1,259	-3.8	-1,191	-3.5
Low-skill female immigrant	-1,038	-3.5	-769	-2.6	-605	-2.1	-774	-2.6	-773	-2.6
Other cities:										
High-skill male native	-182	-0.2	-170	-0.2	-253	-0.3	-451	-0.5	-170	-0.2
High-skill female native	-65	-0.1	-64	-0.1	-94	-0.1	-276	-0.4	-64	-0.1
Low-skill male native	-339	-0.7	-305	-0.7	-346	-0.7	-608	-1.3	-305	-0.7
Low-skill female native	-161	-0.4	-180	-0.5	-205	-0.5	-324	-0.8	-180	-0.5
High-skill male immigrant	-2,200	-2.9	-2,231	-2.9	-2,667	-3.1	-2,888	-3.4	-2229	-2.9
High-skill female immigrant	-1,589	-2.8	-1,616	-2.9	-1,887	-3.1	-2,076	-3.4	-1614	-2.9
Low-skill male immigrant	-587	-1.9	-585	-1.9	-743	-2.2	-974	-2.9	-584	-1.9
Low-skill female immigrant	-425	-1.6	-441	-1.6	-531	-1.9	-676	-2.4	-441	-1.6
Ave. loss/gains without rental income	-466	-0.9	-443	-0.8	-803	-1.5	-1,046	-2.0	-441	-0.8
Welfare with rental income										
High-skill native	701	2.2	718	2.2	613	1.9	369	1.6	718	2.2
Low-skill native	-51	1.5	-28	1.6	-125	1.4	-377	0.8	-27	1.6
High-skill immigrant	-1,577	-2.3	-1,526	-2.3	-1,633	-2.3	-1,873	-2.7	-1,525	-2.3
Low-skill immigrant	-557	-0.1	-527	0.0	-615	-0.3	-849	-1.1	-526	0.0
Ave. loss/gains with rental income	75	1.3	98	1.3	-351	0.4	-594	-0.1	100	1.3

The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Changes in average utility reported in 2015 annual wage dollars. Forced stayer's change in utility measures the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move. Net loss/gains weighted by population share of each group. See text for more details.

Table 10: City Characterization: Increase in Stock of Immigrants

Dependent variation: △% welfare in free migration						
Independent variable:	Housing supply	Local productivity	Local amenity	Share of mobile natives	Share of mobile immigrants	R^2
	[1]	[2]	[3]	[4]	[5]	[6]
High-skill male native	-0.79**	-0.21**	-0.04	0.28**	-0.01	0.60
High-skill female native	-0.91**	-0.10*	-0.12**	0.06	-0.09	0.76
Low-skill male native	-0.45**	-0.20**	-0.03	0.02	-0.54**	0.87
Low-skill female native	-0.32**	-0.16**	0.15**	-0.04	-0.42**	0.61
High-skill male immigrant	-0.43**	-0.25**	0.05	0.1	-0.03	0.29
High-skill female immigrant	-0.79**	-0.09**	-0.24**	0.01	-0.08	0.82
Low-skill male immigrant	-0.48**	-0.20**	-0.11**	0.04	-0.49**	0.88
Low-skill female immigrant	-0.51**	-0.16**	0.06	0.06	-0.49**	0.82

Each regression is weighted by city employment and all variables are standardized. ** and * signify p-value <0.05 and p-value <0.1, respectively.

Table 11: Number of Additional Immigrants by MSA

MSA	Baseline	Percent of reduction		
		20%	50%	80%
Phoenix, AZ	17,457	13,966	8,728	3,491
Tucson, AZ	2,449	1,960	1,224	489
Bakersfield, CA	4,467	3,573	2,233	893
Fresno, CA	6,153	4,921	3,076	1,230
Los Angeles-Long Beach, CA	73,080	58,464	36,540	14,616
Modesto, CA	2,725	2,180	1,363	546
Salinas-Sea Side-Monterey, CA	2,681	2,145	1,340	536
San Diego, CA	11,643	9,313	5,822	2,329
San Francisco-Oakland-Vallejo, CA	12,056	9,646	6,029	2,411
San Jose, CA	6,272	5,017	3,136	1,255
Santa Barbara-Santa Maria-Lompoc, CA	2,588	2,070	1,294	518
Santa Cruz, CA	1,266	1,012	633	253
Santa Rosa-Petaluma, CA	1,947	1,556	973	389
Stockton, CA	3,374	2,700	1,687	675
Ventura-Oxnard-Simi Valley, CA	4,458	3,565	2,229	892
Visalia-Tulare-Porterville, CA	3,322	2,657	1,661	664
Albuquerque, NM	1,844	1,476	923	368
Austin, TX	4,995	3,997	2,498	998
Brownsville-Harlingen-San Benito, TX	1,972	1,577	986	394
Corpus Christi, TX	213	171	106	43
Dallas-Fort Worth, TX	27,039	21,631	13,520	5,407
El Paso, TX	4,212	3,369	2,106	843
Galveston-Texas City, TX	427	342	215	86
Houston-Brazoria, TX	21,543	17,234	10,772	4,308
Kileen-Temple, TX	345	277	172	69
Lubbock, TX	164	132	82	32
San Antonio, TX	4,837	3,870	2,419	967
Riverside-San Bernardino,CA	21,696	17,357	10,848	4,340
Total additional immigrants	245,225	196,178	122,616	49,043
Number of removed immigrants		49,047	122,610	196,182

See text for details on the characteristics of potentially illegal immigrants.

Table 12: Wages: Reduction in Inflow of Immigrants Adjacent to Mexico

	Reduced-immigrant cities								Other cities			
	$\triangle$% annual wage Fixed migration				$\triangle$% annual wage Free migration				$\triangle$% annual wage Free migration			
Percent of reduced immigrant flow	Baseline	20%	50%	80%	Base	20%	50%	80%	Baseline	20%	50%	80%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
High-skill male native	0.27	0.22	0.14	0.05	0.12	0.10	0.06	0.02	0.05	0.04	0.02	0.01
High-skill female native	0.29	0.24	0.15	0.06	0.13	0.11	0.07	0.03	0.05	0.04	0.03	0.01
Low-skill male native	-0.58	-0.47	-0.30	-0.12	-0.27	-0.22	-0.13	-0.05	-0.11	-0.09	-0.06	-0.02
Low-skill female native	-0.09	-0.07	-0.05	-0.02	-0.03	-0.02	-0.02	-0.01	-0.02	-0.02	-0.01	0.00
High-skill male immigrant	0.17	0.14	0.09	0.03	0.08	0.07	0.05	0.02	0.02	0.02	0.01	0.00
High-skill female immigrant	0.24	0.19	0.12	0.05	0.11	0.10	0.06	0.02	0.04	0.03	0.03	0.01
Low-skill male immigrant	-0.98	-0.79	-0.50	-0.20	-0.49	-0.40	-0.24	-0.10	-0.30	-0.24	-0.16	-0.06
Low-skill female immigrant	-0.37	-0.30	-0.19	-0.08	-0.15	-0.11	-0.09	-0.03	-0.13	-0.11	-0.06	-0.03
Housing rents	0.70	0.56	0.35	0.14	0.34	0.27	0.17	0.07	0.11	0.09	0.06	0.02

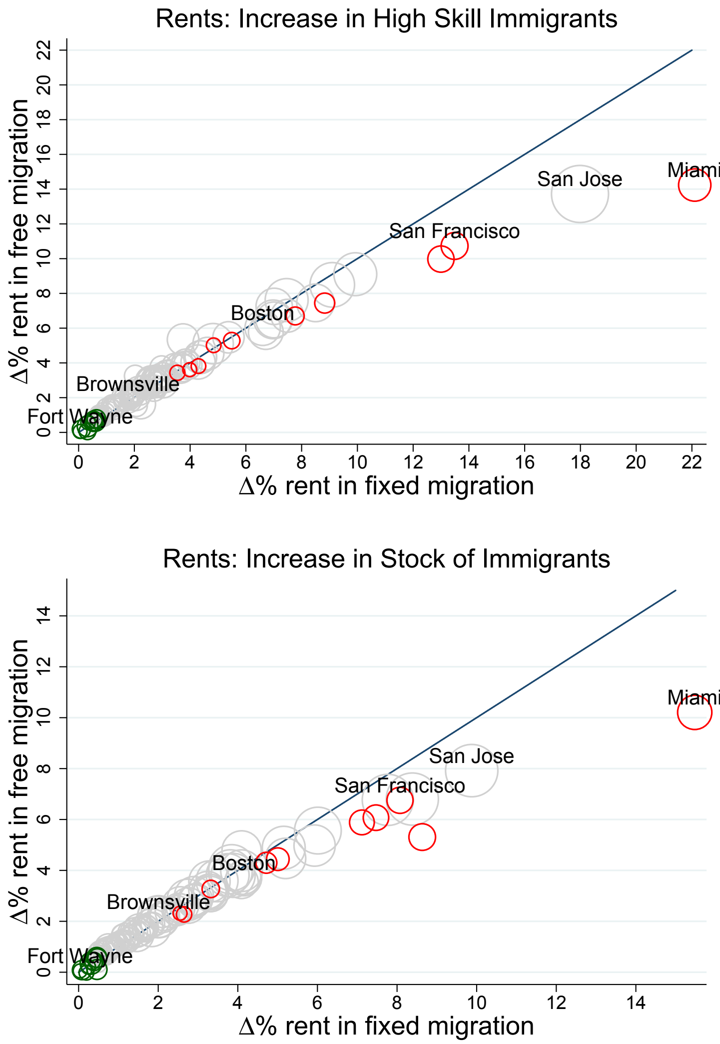
Reduced-immigrant cities are MSAs in California, Texas, Arizona and New Mexico. Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. All changes are relative to the initial wages where there is no additional immigrants. Fixed-migration change measures the difference between the initial wages and the wages when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table 13: Welfare: Border Wall Effects

	△$ ave. utility							
	Fixed migration				Free migration			
Percent of reduced immigrant flow	Baseline	20%	50%	80%	Baseline	20%	50%	80%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Natives in reduced-immigrant cities:								
High-skill male	70	56	35	14	28	21	14	5
High-skill female	65	52	33	13	26	21	13	5
Low-skill male	-341	-274	-172	-69	-152	-123	-76	-31
Low-skill female	-95	-76	-47	-19	-41	-32	-22	-8
Immigrants in reduced-immigrant cities:								
High-skill male	-59	-47	-29	-12	-41	-31	-18	-7
High-skill female	-13	-10	-7	-3	-18	-10	-9	-3
Low-skill male	-375	-301	-190	-77	-173	-139	-87	-35
Low-skill female	-160	-129	-81	-33	-70	-55	-37	-14
Natives in other cities:								
High-skill male	0	0	0	0	14	12	7	3
High-skill female	0	0	0	0	13	11	7	3
Low-skill male	0	0	0	0	-65	-52	-32	-13
Low-skill female	0	0	0	0	-20	-16	-9	-4
Immigrants in other cities:								
High-skill male	0	0	0	0	-18	-15	-9	-4
High-skill female	0	0	0	0	-2	-3	-1	0
Low-skill male	0	0	0	0	-96	-76	-49	-19
Low-skill female	0	0	0	0	-44	-36	-21	-9
Ave. loss/gains without rental income	-17	-13	-8	-3	-24	-19	-12	-5
Welfare with reduction in rental income:								
High-skill native	62	49	31	12	67	54	33	12
Low-skill native	-19	-15	-10	-4	-38	-30	-19	-4
High-skill immigrant	20	16	10	4	20	16	10	4
Low-skill immigrant	-73	-58	-37	-15	-83	-66	-42	-15
Ave. loss/gains with rental income	13	11	7	3	7	6	4	3

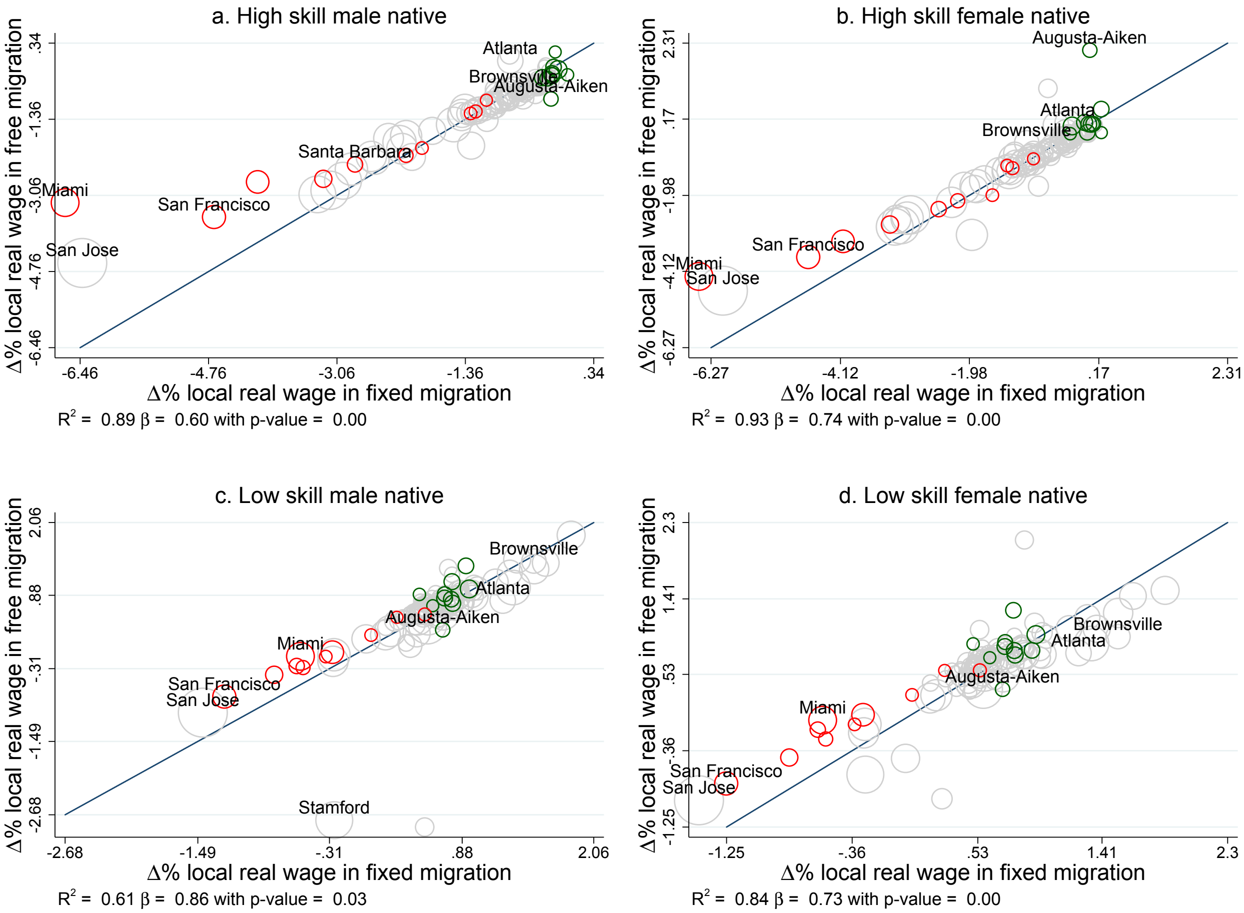
The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Changes in average utility reported in 2015 annual wage dollars.

Figure 1: Cities' Rent Distribution



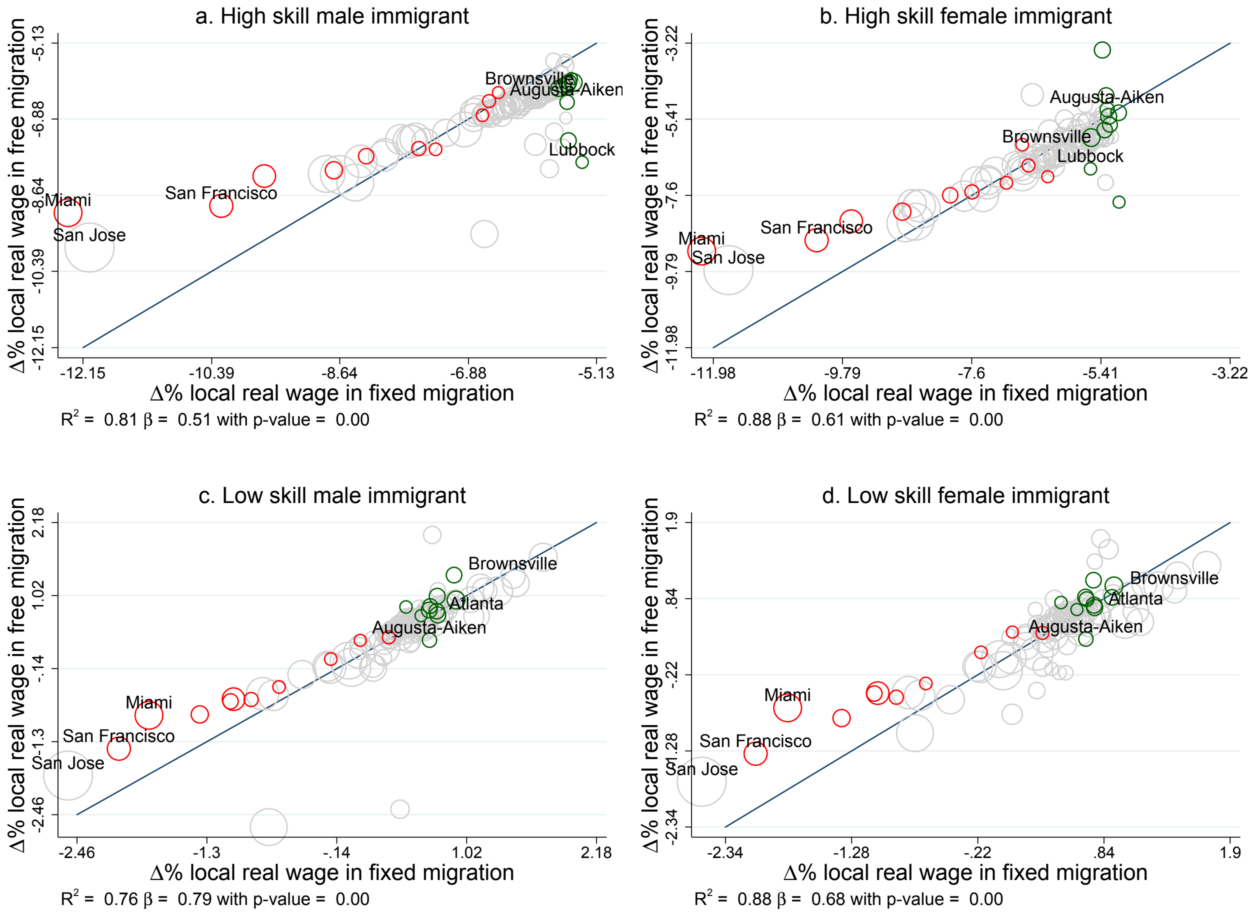
Local rent in 2015 dollars. Fixed-migration change measures the difference between the initial rents and the rents when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial rents and the rents after all workers simultaneously choose locations. Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply.

Figure 2: Native Local Real Wages: Increase in High Skill Immigrants



Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial local real wages to the fixed-migration local real wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial local real wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply. See text for more details.

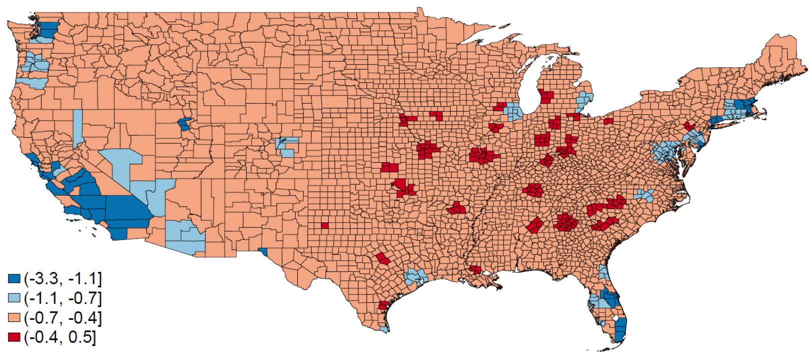
Figure 3: Immigrant Local Real Wages: Increase in High Skill Immigrants



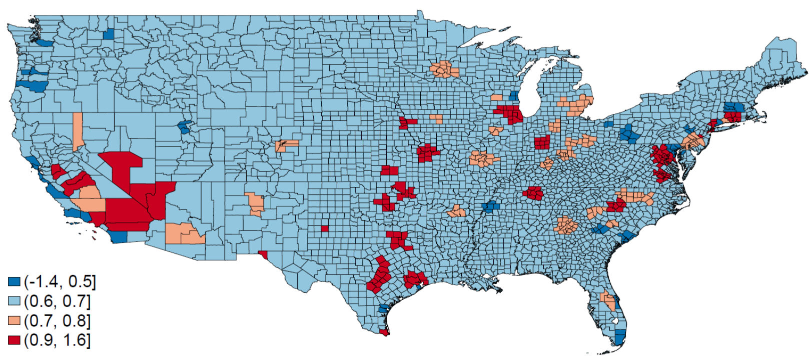
Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial local real wages to the fixed-migration local real wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial local real wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply. See text for more details.

Figure 4: Welfare Impact on Natives: Increase in High Skill Immigrants

(a) Percentage Change in Welfare: High Skill Natives



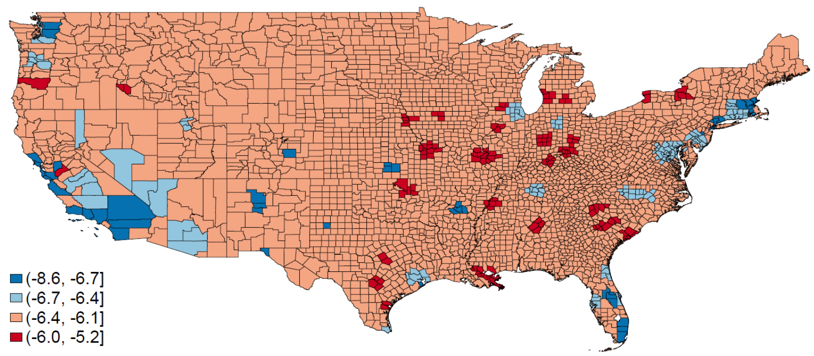
(b) Percentage Change in Welfare: Low Skill Natives



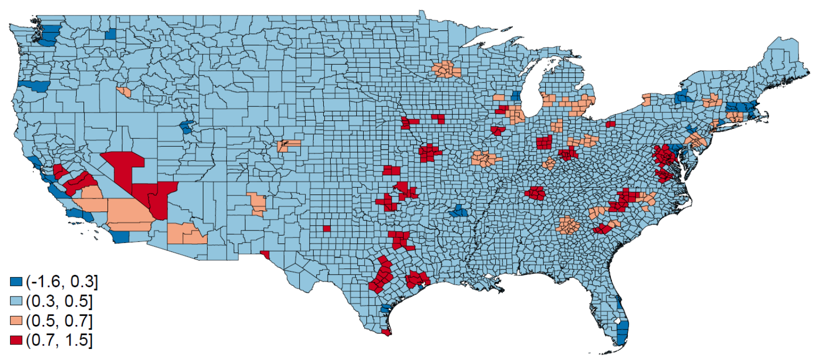
These maps show quartiles of the percentage change from the initial average utility to the free-migration utility across the 114 MSAs which have the highest immigrant population from 1990-2007. The remaining cities are combined as the outside option, or "non-popular destination for immigrants". This group also includes Alaska and Hawaii which are not shown on the maps for readability.

Figure 5: Welfare Impact on Immigrants: Increase in High Skill Immigrants

(a) Percentage Change in Welfare: High Skill Immigrants

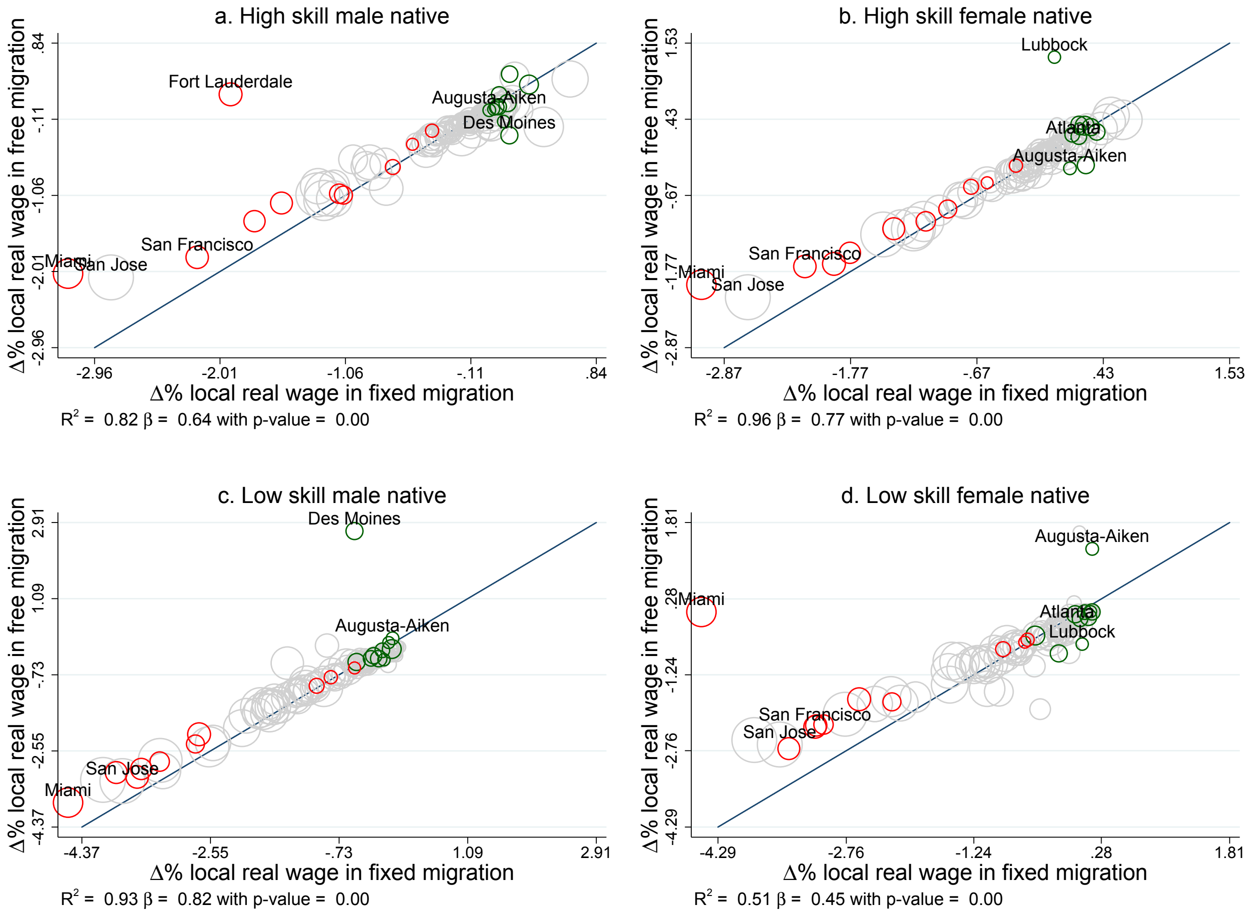


(b) Percentage Change in Welfare: Low Skill Immigrants



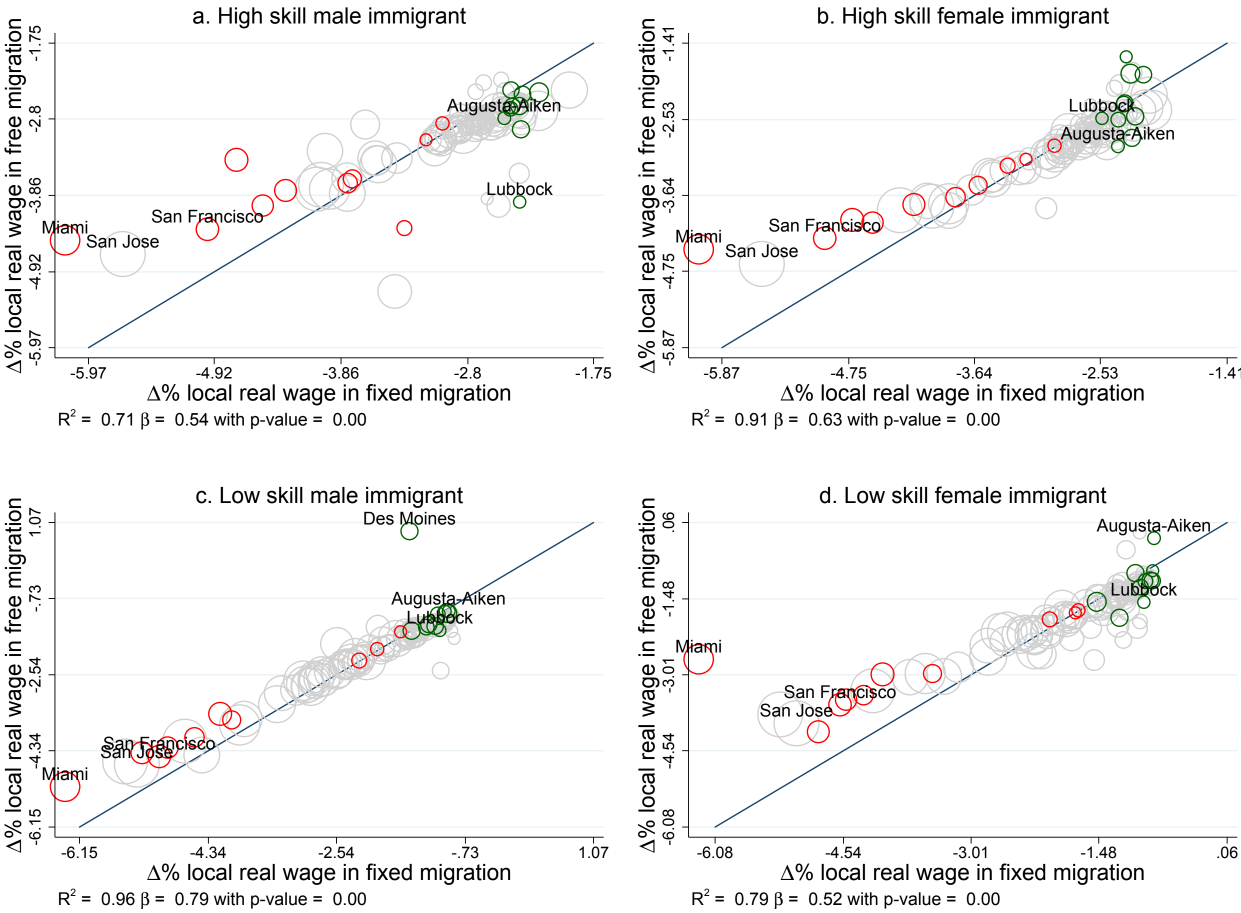
These maps show quartiles of the percentage change from the initial average utility to the free-migration utility across the 114 MSAs which have the highest immigrant population from 1990-2007. The remaining cities are combined as the outside option, or "non-popular destination for immigrants". This group also includes Alaska and Hawaii which are not shown on the maps for readability.

Figure 6: Native Local Real Wages: Increase in the Stock of Immigrants



Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial local real wages to the fixed-migration local real wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial local real wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply. See text for more details.

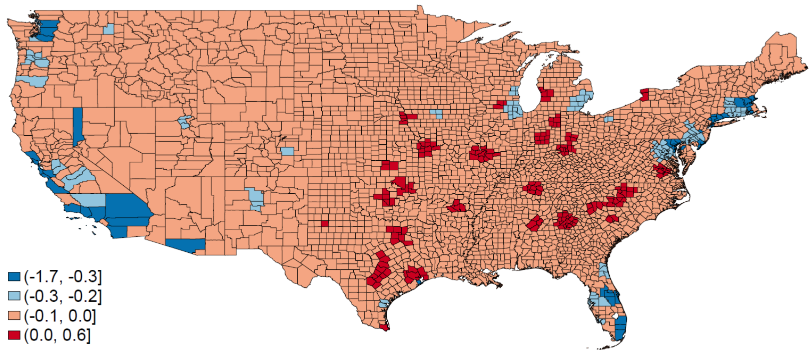
Figure 7: Immigrant Local Real Wages: Increase in the Stock of Immigrants



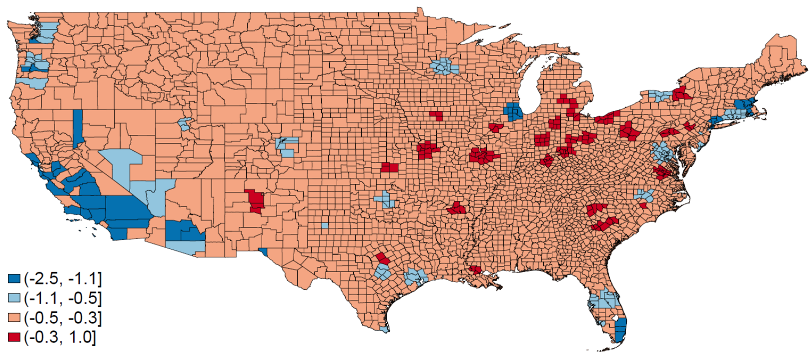
Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial local real wages to the fixed-migration local real wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial local real wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply. See text for more details.

Figure 8: Local Real Wage Impact on Natives: Increase in the Stock of Immigrants

(a) Percentage Change in Local Real Wage: High Skill Natives



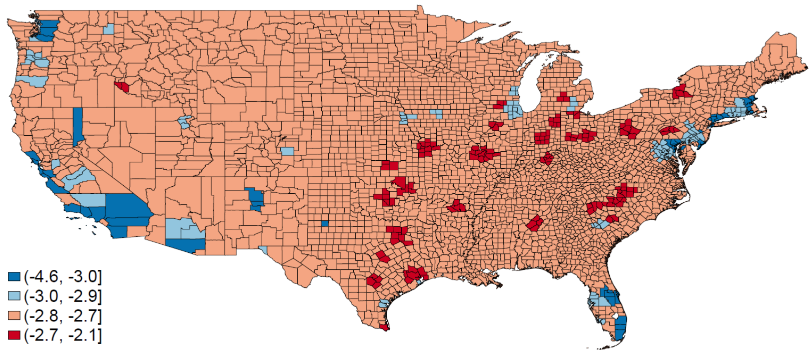
(b) Percentage Change in Local Real Wage: Low Skill Natives



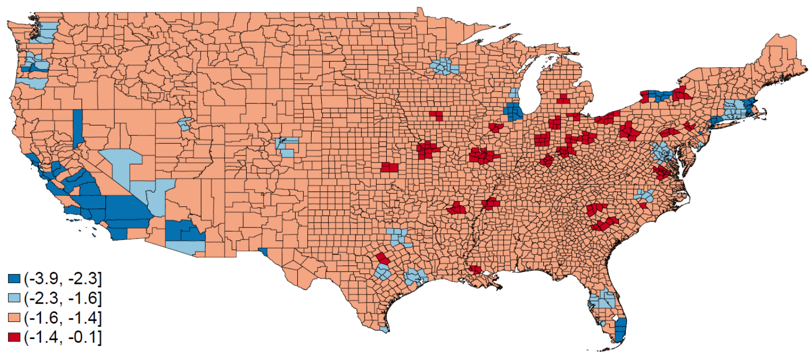
These maps show quartiles of the percentage change from the initial average utility to the free-migration utility across the 114 MSAs which have the highest immigrant population from 1990-2007. The remaining cities are combined as the outside option, or "non-popular destination for immigrants". This group also includes Alaska and Hawaii which are not shown on the maps for readability.

Figure 9: Local Real Wage Impact on Immigrants: Increase in the Stock of Immigrants

(a) Percentage Change in Local Real Wage: Immigrants



(b) Percentage Change in Local Real Wage: Low Skill Immigrants



These maps show quartiles of the percentage change from the initial average utility to the free-migration utility across the 114 MSAs which have the highest immigrant population from 1990-2007. The remaining cities are combined as the outside option, or “non-popular destination for immigrants”. This group also includes Alaska and Hawaii which are not shown on the maps for readability.

Online Appendix

A. Data

Labor Supply

Workers in the sample are restricted to individuals over the age of 18 with 1 to 40 years of potential experience who report positive earnings, not currently enrolled in schools and worked at least one week in the previous year. Labor supply is a count of employed people multiplied by the individual's person weight. Years of potential experience are calculated using the difference between current age and the age at which the individual entered the labor force. I assume that high school dropouts enter the labor force at age 17, high school graduates enter at 19, people with some college education enter at 21, and people with at least a college degree enter at 23. Immigrants are defined as individuals born abroad. High skill workers are defined as as those with 1–3 years of college or more. Low skill workers include high school graduates and dropouts.

Wages

The wage sample is a subset of the employment sample where workers who are self-employed and workers who work less than 35 hours a week and 40 weeks per year are eliminated. Cities' wages are deflated using the CPI-U index to 2015 dollars. Topcoded wages are multiplied by 1.5. Wages are constructed by calculating the real hourly wages of individuals and taking their weighted average where the weights are the hours worked by the individual times person weight.

Networks

Immigrant networks are measured by the number of previous immigrants in the past decade from each country group. For the network size in 1990, 2000 and 2005-7, I include all individuals born outside the U.S. living in each MSA in 1980, 1990 and 2000, respectively.

The distance from natives' states of birth to each MSA is calculated as a distance from the population centroid in each state to the the population centroid in each MSA. The Census website provides latitudes and longitudes of population centroids at the state and county levels, but not at the MSA level. I use the average latitudes and longitudes of population centroids from all counties located in a given MSA as the population centroid.

Rents and other Variables

City rents are measured as the average gross annual rent (which includes both the housing rent and the cost of utilities) per household member. For households owning houses, I impute rents from housing values using a discount rate of 7.85 percent (Peiser and Smith, 1985) where annual expenditures for utilities are added to obtain gross imputed rent.

Additional data on land-use regulations and land unavailability are taken from Saiz (2010). The price of national goods is set at the CPI-U index of all goods measured in 2015 dollars.

B. Characteristics of Immigrants

Table A.3 reports the numbers of immigrants and educational attainment by country of origin, respectively. Nearly 40 percent of immigrants are from Mexico and Central America, with 70 to 80 percent having at most a high school education. Large fractions of Immigrants from Europe, India, Japan and China, on the other hand, have at least college degrees.

C. Existence and Uniqueness

The proof of existence is based on Bayer and Timmins (2005). Eq (18)-(22) implicitly define the vector of population $\overline{Z}_t = \Sigma_{i\in\mathscr{Z}_t}\text{Pr}_{it}$ that maps $[0,Z_t]^C$ into itself where Z_t is the total population of type-z workers and C is the number of cities in the choice set. An equilibrium is a fixed point,

$$\overline{Z}_t^* = g\left(\overline{Z}_t^*, \Omega\right) \equiv \Sigma_{i\in\mathscr{Z}_t}\text{Pr}_{it}$$

where Ω is the vector of parameters. The following proposition provides sufficient conditions under which a fixed point of to the above equation exists.

Proposition 1. *If (i) ε_{ict} is drawn from a continuous well-defined distribution function, (ii) each consumer's utility u_i is continuous in $\overline{Z}_t$ and (iii) each firm's production possibility set y_j is closed, bounded, convex and $0 \in y_j \subseteq \mathbb{R}^n$, then an equilibrium exists.*

Proof. Assumption (iii) and the continuity of the firm's objective function ensure that the solution to (21) exists. Assumptions (i) and (ii) imply that the mapping g is a continuous mapping of a closed and bounded interval into itself. By the Brouwer fixed-point theorem, there exists a fixed point of this mapping g. □

Given that ε_{ict} is drawn from a Type I Extreme Value distribution, it is continuous; u_i is continuous; and the firms' production possibility set satisfies (iii), thus Proposition 1 implies that an equilibrium exists.

As discussed in Bayer and Timmins (2005), the uniqueness of an equilibrium depends on the following features of the problem: (i) the magnitude of the agglomeration and congestion forces; (ii) the total number of cities; (iii) the importance of individual tastes in the utility function; and (iv) the variation and importance of fixed attributes across cities such as home premiums and network values. Bayer et al. (2004) and Bayer and Timmins (2005) show that a congestion effect gives rise to a unique equilibrium. The present model incorporates a congestion force through housing supply.

A congestion effect causes workers to disperse which preserves the preference rank-ordering of locations. However, a sufficiently strong agglomeration effect can alter the rank-order of locations leading to multiple equilibria. In the present framework, network values are measured by the numbers of previous immigrants and independent of the current number of immigrants in a given city. So there is no agglomeration incentive due to current networks for immigrants. However, complementarity between labor types may induce some workers to cluster in the same locations. Nonetheless, if the housing supply congestion effect is sufficiently strong, a unique equilibrium can be obtained.

Given the number of parameters, the restrictions on the model primitives for which a unique equilibrium arises cannot be easily characterized. However, as noted in Bayer and Timmins (2005), it is possible to verify whether an equilibrium is unique. Consider the two sequences defined by $\left\{\overline{Z}_t, g\left(\overline{Z}_t\right), g\left(g\left(\overline{Z}_t\right)\right), \ldots\right\}$ starting at the endpoints of $\overline{Z}_t$. If an agglomeration effect induces multiple equilibria, then these sequences converge to at least two points. So one may verify uniqueness by applying $g(.)$ iteratively starting near the endpoints of $\overline{Z}_t$ and determining whether the sequences converge to distinct fixed points.

D. Sensitivity Analysis of Estimation

Panel I of Table A.7 reports the estimated substitution elasticities using various measures of wages and labor supply as well as different specifications. The first column reports the estimates of labor demand parameters in the baseline case. The second column reports the substitution elasticities when immigrants with more than thirty years in the U.S. are classified as natives. In this case, the elasticities of substitution are close to the baseline estimates. The third column reports the substitution elasticities using a different measure of labor supply. I adopt Card (2009)'s relative numbers of efficiency units by defining the labor supply of low skill workers as the sum of high school graduates, plus 0.7 times the number of dropouts and plus 0.6 times the number of people with 1–3 years of college education. For high skill labor, I define this as the sum of college graduates plus 0.4 times the number of people with 1–3 years of college education. This yields the elasticities of substitution between immigrants and natives that are slightly higher than my estimates. The elasticity of substitution between high and low skill increases to 3.51 which is closer to Card (2009)'s estimate. In the baseline case, I do not adjust the labor supply of each skill group by their relative efficiency units in order to keep the number of worker types in the counterfactuals manageable. However, in Section 6.6, I examine the sensitivity of counterfactual policy experiments when the substitution elasticity between high and low skill labor increases.

The forth column reports the substitution elasticities using wage residuals. I residualize wages against worker's age, age squared and detailed level of education separately for each group of workers. This yields elasticities that are similar to the benchmark model. Additionally, I examine whether the substitution elasticities are sensitive to the ordering of the CES production function. I reverse the order by placing gender on the top and skill on the second level. As shown in the last column, the elasticity of substitution between high and low skill labor becomes larger. However, in all of these specifications, my estimates indicate imperfect substitutability between natives and immigrants.

Finally, one may be concerned that the initial immigrant shares used in (26) are correlated with unobserved factors in a city, even if the national inflow rates are exogenous. As discussed in Card (2009), given the large inflows of Mexican immigrants in the past, the instruments are highly correlated with a city's fraction of Mexican immigrants in 1980. I have re-estimated the elasticities of substitution between immigrants and natives by removing Mexican immigrants from the IV construction. I find that the elasticity of substitution between immigrants and natives of high skill labor remains roughly the same ($\sigma_{M,H} = 6.96$), while the substitutability among low skill labor becomes slightly larger ($\sigma_{M,L} = 20.62$).

Panel II displays the elasticity of workers' demand for a city with respect to local real wage, λ_z^w. Recall that in the second step of worker preference estimation, I define changes in local real wage on the RHS of (**??**) as prices relative to the outside option. Since the mean utilities in the first step of the estimation are identified relative to the outside option, it is consistent to use relative prices in the second step. When prices are not expressed in relative terms, the estimates of λ_z^w become considerably smaller for all groups of workers as shown in the second column of Panel II. Further, the Hansen-J test of over-identification rejects the hypothesis that my instruments are jointly uncorrelated with changes in unobserved local amenity with p-values less then 0.05. The third column reports the estimates of λ_z^r using different housing expenditure shares. I take local goods expenditure shares from Moretti (2013) and set λ_z^r to be 0.62 for all types of workers. The estimates of worker preferences λ_z^w become considerably smaller and I reject the hypothesis that changes in unobserved local amenity are uncorrelated with my instruments with p-values less then 0.05.

Panel III presents estimates of housing supply elasticities under different specifications. The first column shows the baseline estimates. The second column shows the estimates when the measure of geographic constraints are interacted with predetermined initial log city population in 1980.[52] The coefficient on geographic constraints interacted with predetermined population has a

[52]As noted in Saiz (2010), geographic constraints are more likely to be binding when the level of construction is high.

negative sign. This leads to the counter-intuitive interpretation that geographic constraints matter less when population increases, and the Hansen-J test rejects the null hypothesis that changes in unobserved local construction costs are uncorrelated with my instruments with p-values less then 0.05. The third column shows the estimates when the values of rents of home owners are imputed using a higher discount rate, 0.1 (Mills, 1990). The estimates are not sensitive to the imputation of rents.

E. Sensitivity of Counterfactual Analyses

In this section, I examine the sensitivity of counterfactual analyses using the estimates of labor demand at the national level from Ottaviano and Peri (2012). In their specification with fixed effect controls, Ottaviano and Peri (2012) estimate the elasticities of substitution between immigrants and natives to be 11.9 among high school dropouts, 10.1 among high school graduates, and 14.7 among workers with some college education. Further, they estimate the substitution elasticity between immigrants and natives who have college degrees to be 111.1; however, this estimate is not precise.

Since my model divides workers into high and low skill labor, I set the elasticity of substitution between immigrants and natives of high skill σ_{M-H} to be the average of the immigrant-native substitution elasticities of workers with some college education and with college degrees, weighted by their working-age population shares. This gives an elasticity of 57.6. Similarly, I set the elasticity of substitution between immigrants and natives of low skill σ_{M-L} to be the weighted average of immigrant-native substitution elasticities among high school dropouts and high school graduates: 11. I set the elasticity of substitution between high and low skill labor is to 2 which is close to the baseline estimate in my paper. As Ottaviano and Peri (2012) only include males in their sample for this specification, I assume male and female workers to be perfect substitutes, but allow for differences in productivity levels (β^{S}_{egct}).

Tables A.11 and A.12 display the changes in wages, rents, and welfare in the skill selective immigration policy using Ottaviano and Peri (2012)'s national labor demand estimates. The second last two rows of Table A.12 report the national average welfare loss/gains with and without rental income. While the overall net loss/gains without rental income are similar to my baseline case, the welfare and wage changes of high skill workers are strikingly different. Ottaviano and Peri (2012) estimate the substitutability between natives and immigrants amongst high skill labor to be substantially higher than my estimate. Further, they find immigrants and natives to be closer substitutes among high skill labor than low skill, while Card (2009) and I find the reverse at the city level.[53] The wage and welfare effects on low skill workers are similar to the baseline case given

[53] Card (2009) estimates the elasticity of substitution between immigrants and natives to be higher than my estimates

that our estimates of the substitutability between high and low skill labor are similar. However, the higher degree of substitutability between high skill immigrants and high skill natives leads to adverse wage and welfare impacts on high skill natives. The negative wage and welfare impacts among high skill immigrants are less severe as the impacts are diffused across a bigger group of workers.

Using Ottaviano and Peri (2012)'s national labor demand estimates in the second counterfactual, the wage and welfare effects of immigration on low skill natives are slightly attenuated, but stronger for low skill immigrants (see Tables A.13 and A.14). This is because Ottaviano and Peri (2012)'s estimates for the elasticities of substitution between low skill immigrants and low skill natives are lower than mine. Similarly, the gains are more equalized across all high skill workers. The positive wage impacts on high skill natives become much smaller, hence the average welfare losses on high skill natives are intensified. Therefore, while the "national average welfare change" is not very sensitive, the positive wage effects of immigration on high skill natives become much lower when using the labor demand estimates at the national level.

Additionally, I examine whether the results of counterfactual analyses are sensitive to the ordering of the nested-CES production function. Table A.15-A.18. show the wage and welfare effects of each counterfactual when I reverse the order of gender and skill in the production function. As shown previously in Table A.7, the elasticity of substitution between high and low skill labor becomes larger while the substitutability between genders remain roughly the same. In the skill selective immigration policy, this leads to a slightly larger increase in the wages of low skill workers. But overall, the welfare effects in the skill selective and skill neutral immigration policies are reasonably close to the baseline. Finally, I also ran all counterfactuals using the estimates of workers' marginal utility with respect to local real wage from Diamond (2016). This involves setting λ_z^w to be 2.12 for high skill native, 4.03 for low skill natives, 3.06 for high skill immigrants and 4.33 for low skill immigrants. The results are similar qualitatively, but the migration responses among low skill workers are stronger as they are estimated to be more sensitive to changes in prices, relative to my results.

for both skill groups. This would imply larger wage effects of immigration on natives, but qualitatively our results would be similar.

Table A.1: Summary Statistics: Levels

	1990				2000				2007			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Ln natives' wages												
High-skill male	3.46	0.14	3.02	3.97	3.58	0.16	3.17	4.36	3.67	0.20	3.24	4.80
High-skill female	3.08	0.12	2.87	3.50	3.23	0.14	2.94	3.87	3.32	0.16	3.03	4.13
Low-skill male	3.06	0.13	2.63	3.40	3.09	0.12	2.70	3.39	3.07	0.12	2.73	3.50
Low-skill female	2.76	0.12	2.43	3.08	2.86	0.12	2.54	3.24	2.86	0.13	2.49	3.17
Ln immigrants' wages												
High-skill male	3.46	0.18	2.98	3.85	3.55	0.18	3.01	4.18	3.60	0.22	3.01	4.51
High-skill female	3.07	0.16	2.64	3.50	3.23	0.14	2.96	3.74	3.29	0.19	2.80	3.82
Low-skill male	2.88	0.20	2.43	3.36	2.83	0.13	2.50	3.26	2.77	0.15	2.43	3.45
Low-skill female	2.62	0.17	2.20	3.02	2.67	0.13	2.25	2.93	2.61	0.14	2.14	2.97
Ln rent	8.97	0.20	8.54	9.54	8.94	0.17	8.59	9.67	9.13	0.22	8.73	10.02

The sample include a balanced panel of 115 MSA's across three censuses which have at least 200 full-time and non self-employed of all types of workers. Hourly wages and annual rents are measured in logs and expressed in 2015 dollars.

Table A.2: Immigration at City Level

1990		2000		2007	
Top 15 MSAs	Percent Immigrants	Top 15 MSAs	Percent Immigrants	Top 15 MSAs	Percent Immigrants
Miami-Hialeah, FL	54.9	Miami-Hialeah, FL	62.5	Miami-Hialeah, FL	62.7
Los Angeles, CA	39.2	Los Angeles, CA	47.2	San Jose, CA	49.5
McAllen-Edinburg, TX	35.9	San Jose, CA	44.4	Salinas-Sea, CA	47.1
Salinas-Sea, CA	34.9	Salinas-Sea, CA	42.3	Los Angeles, CA	44.8
El Paso, TX	34.4	McAllen-Edinburg, TX	41.2	New York-NE, NJ	41.4
Brownsville, TX	29.8	New York-NE, NJ	39.0	Fort Lauderdale, FL	40.5
San Jose, CA	29.2	Visalia-Tulare, TX	37.7	Visalia-Tulare, TX	39.6
New Bedford, MA	28.2	El Paso, TX	36.3	McAllen-Edinburg, TX	39.2
Visalia-Tulare, TX	27.6	San Francisco, CA	35.8	San Francisco, CA	38.6
New York-NE, NJ	26.5	Brownsville, TX	35.6	Stockton, CA	37.3
Stamford, CT	25.4	Fort Lauderdale, FL	35.3	Santa Barbara, CA	37.3
San Francisco, CA	25.2	Santa Barbara, CA	33.3	El Paso, TX	36.8
Ventura-Oxnard, CA	24.6	Ventura-Oxnard, CA	32.8	Yakima, WA	36.4
Fresno, CA	23.9	Fresno, CA	32.8	Stamford, CT	35.2
Santa Barbara, CA	23.5	Riverside, CA	29.8	Riverside, CA	34.0

Percent immigrants expressed in terms of city's working-age population which includes people aged 18 or older with 1 to 40 years of potential experience. Immigrants are individuals born abroad.

Table A.3: Characteristics of Immigrants and Natives

	Working-age population (thousands)			Share of US population		
	1990	2000	2007	1990	2000	2007
All U.S.	133,698	155,429	165,553	100.0	100.0	100.0
Natives	119,380	131,765	136,732	89.3	84.8	82.6
Immigrants	14,318	23,664	28,821	10.7	15.2	17.4

	Share of working-age immigrants (percent)			Share of working-age natives (percent)			Immigrant to native working-age ratio		
	1990	2000	2007	1990	2000	2007	1990	2000	2007
Dropouts	28.3	27.4	24.8	10.9	7.9	6.6	0.30	0.60	0.81
High School	25.5	29.7	31.1	35.5	40.4	39.0	0.08	0.13	0.17
Some College	22.5	16.5	15.6	31.0	25.1	25.6	0.08	0.11	0.13
College	23.7	26.4	28.5	22.6	26.6	28.8	0.12	0.17	0.21
Female	42.4	41.4	40.3	46.2	47.4	47.1	0.11	0.15	0.18
Male	57.6	58.6	59.7	53.8	52.6	52.9	0.12	0.19	0.24

Working-age population includes people aged 18 or older with 1 to 40 years of potential experience. Immigrants are individuals born abroad.

Table A.4: Educational Attainment and Networks of Immigrants in 2007

Country group	Share of all immigrants	No. of cities with large networks	Educational Attainment			
			Dropout	High school	Some college	College
Mexico	31.8	60	53.6	33.7	7.8	4.9
Central America	7.8	23	44.0	33.6	12.5	9.9
Central Europe	7.6	44	5.0	32.1	22.4	40.6
South America	6.8	22	11.7	38.0	20.6	29.7
Caribbean	6.2	17	17.3	41.6	21.8	19.4
India	5.4	18	5.6	14.5	9.5	70.4
China	4.7	17	11.0	21.3	12.5	55.3
Philippines	4.4	18	3.5	21.2	25.4	49.9
Africa	3.7	17	8.3	28.6	22.5	40.6
Vietnam	3.0	19	19.0	35.0	20.4	25.5
Japan and East Asia	2.7	14	3.6	24.6	18.8	53.0
Canada and Other North America	2.1	22	4.6	24.4	24.3	46.7
UK and Ireland	2.1	19	2.5	26.5	24.9	46.1
Southern Europe	2.0	17	15.9	38.2	17.1	28.8
Cuba	1.9	8	11.5	43.0	19.5	26.0
Middle East	1.9	11	10.9	30.7	17.8	40.6
Other Southeast Asia	1.9	19	18.2	32.7	19.8	29.3
Korea	1.3	9	2.4	21.9	27.2	48.6
Other Southwest Asia	1.1	6	4.9	22.4	18.4	54.3
Western Europe	0.9	7	1.8	19.9	22.6	55.6
Australia and New Zealand	0.5	4	7.4	34.2	20.6	37.7
Northern Europe	0.3	2	1.9	18.3	25.9	53.9

Working-age population includes people aged 18 or older with 1–40 years of potential experience. Immigrants are individuals born abroad. The shares and education attainment of immigrants and drawn from the combined 2005-7 ACS. The number of cities with large networks represent MSAs in the estimation sample which have at least 10,000 immigrants from each country group in year 2000. The estimation sample consist of 115 cities which have at least 200 full-time and non-self employed of each type of workers.

Table A.5: First Stage: Labor Demand Estimations

	Labor Demand			
	skill	gender	high-skill nativity	low-skill nativity
	[1]	[2]	[3]	[4]
Year dummy	yes	yes	yes	yes
High skill dummy	no	-0.075	no	no
		(0.005)		
Male dummy	no	no	-0.068	0.139
			(0.041)	(0.072)
Transitory shocks, KM_{egct}	0.290	0.057	-1.182	-2.584
	(0.025)	(0.005)	(0.129)	(0.416)
Wage residual 1980, ψ_{1980}	0.871	-0.009	0.642	0.1457
	(0.073)	(0.023)	(0.179)	(0.362)
$\log(\text{pop}_{1980})$	-0.033	-0.009	0.070	-0.020
	(0.007)	(0.002)	(0.019)	(0.035)
Predicted inflow of immigrants	0.129	1.883	-141.592	-38.932
	(0.012)	(0.157)	(5.354)	(2.367)
Constant	0.323	0.288	3.330	2.649
	(0.084)	(0.028)	(0.222)	(0.443)
R^2	0.325	0.275	0.638	0.411
t-statistics	11.20	11.97	-26.45	-16.44
Elasticity of Sub. (OLS)	-8.264**	-15.922**	7.960**	13.957**
	(0.002)	(0.011)	(0.001)	(0.001)
Baseline Elasticity of Sub. (IV)	2.193**	1.973**	6.925**	17.870**
	(0.109)	(0.167)	(0.154)	(0.819)

The table reports the coefficients from the first stage regressions of labor demand estimations as well as the OLS estimates. Standard errors in parentheses. t-statistics: test whether the coefficient of the predicted inflow equals zero. See text for more details.

Table A.6: Changes in Annual Wages: Mariel Boatlift

	△ annual wage in free migration											
	Miami		Atlanta		Houston		Los-Angeles		Tampa		Other cities	
	△$	△%	△$	△%	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
High-skill male native	155	0.22	9	0.01	28	0.04	48	0.06	13	0.02	14	0.02
High-skill female native	108	0.22	7	0.01	19	0.04	35	0.06	10	0.02	10	0.02
Low-skill male native	-98	-0.26	-7	-0.02	-28	-0.07	-31	-0.06	-8	-0.02	-9	-0.02
Low-skill female native	-59	-0.18	-3	-0.01	-3	-0.01	-27	-0.07	-5	-0.02	-3	-0.01
High-skill male immigrant	62	0.12	-41	-0.07	-22	-0.03	-5	-0.01	-33	-0.05	-29	-0.04
High-skill female immigrant	53	0.13	-26	-0.06	-15	-0.03	0	0.00	-18	-0.05	-16	-0.03
Low-skill male immigrant	-137	-0.42	-38	-0.11	-49	-0.17	-47	-0.14	-42	-0.13	-53	-0.14
Low-skill female immigrant	-80	-0.31	-33	-0.10	-22	-0.09	-36	-0.14	-30	-0.11	-31	-0.11
Housing rents	36	0.85	2	0.03	3	0.07	11	0.20	2	0.06	3	006

Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table A.7: Sensitivity Analysis of Parameters

I. Labor Demand					
Substitution elasticity	Baseline	Only immigrants with < 30 yrs in US	Efficiency unit of labor	Residualized wage	Re-ordered gender-skill
	[1]	[2]	[3]	[4]	[5]
σ_{M-L}: low-skill nativity	17.870**	22.441**	20.588**	18.369**	17.870**
	(0.819)	(1.384)	(0.949)	(0.783)	(0.725)
σ_{M-H}: high-skill nativity	6.925**	7.007**	7.272**	10.482**	6.925**
	(0.154)	(1.772)	(0.202)	(0.319)	(0.147)
σ_G: gender	1.973**	2.00**	1.756**	2.609**	2.115**
	(0.167)	(0.167)	(0.128)	(0.176)	(0.222)
σ_E: skill	2.193**	1.966**	3.509**	2.240**	3.183**
	(0.109)	(0.085)	(0.246)	(0.098)	(0.161)
II. Worker Preferences					
	Baseline	Non-relative local real wage	Different housing exp. shares		
High skill male natives	2.086**	1.035**	0.668**		
	(0.253)	(0.082)	(0.055)		
High skill female natives	1.018**	0.369**	0.301**		
	(0.801)	(0.102)	(0.07)		
Low skill male natives	1.323**	0.54**	0.402**		
	(0.071)	(0.136)	(0.082)		
Low skill female natives	1.725**	0.476**	0.386**		
	(0.064)	(0.12)	(0.082)		
High skill male immigrants	3.839**	1.61**	1.114**		
	(0.408)	(0.037)	(0.025)		
High skill female immigrants	3.825**	1.112**	0.871**		
	(0.218)	(0.024)	(0.019)		
Low skill male immigrants	1.228**	0.554**	0.474**		
	(0.131)	(0.048)	(0.03)		
Low skill female immigrants	2.964**	0.963**	0.831**		
	(0.188)	(0.028)	(0.02)		
Hansen's J p-value	0.070	0.004	0.002		
III. Housing Supply Elasticities					
	Baseline	With pop interaction term	With different rent imputation		
Geo	0.909**	9.131**	0.929**		
	(0.121)	(0.831)	(0.177)		
Regulation	0.526**	0.406**	0.493**		
	(0.040)	(0.050)	(0.542)		
Geo*Pop	-	-0.590**	-		
		(0.062)			
Hansen's J p-value	0.207	0.048	0.223		

Standard errors in parentheses, computed using 100 bootstrapped samples. **p<0.05, *p<0.1.

Table A.8: City Characteristics: Productivity, Housing Supply, Share of Mobile Workers

Highest city-specific productivity	Lowest city-specific productivity
Stamford, CT	Brownsville-Harlingen-San Benito, TX
San Jose, CA	Kileen-Temple, TX
Bridgeport, CT	El Paso, TX
San Francisco-Oakland-Vallejo, CA	Lubbock, TX
New York-Northeastern NJ	Pensacola, FL
Washington, DC/MD/VA	Fayetteville, NC
Trenton, NJ	Fort Wayne, IN
Boston, MA-NH	Boise City, ID
Santa Cruz, CA	Greensboro-Winston Salem-High Point, NC
Hartford-Bristol-Middleton- New Britain, CT	Augusta-Aiken, GA-SC
Most inelastic housing supply	Least inelastic housing supply
Ventura-Oxnard-Simi Valley, CA	Fort Wayne, IN
Miami-Hialeah, FL	Wichita, KS
Santa Rosa-Petaluma, CA	Augusta-Aiken, GA-SC
Boston, MA-NH	Kileen-Temple, TX
Santa Barbara-Santa Maria-Lompoc, CA	Greenville-Spartanburg-Anderson SC
Worcester, MA	Des Moines, IA
San Francisco-Oakland-Vallejo, CA	Brownsville-Harlingen-San Benito, TX
Fort Lauderdale-Hollywood-Pompano Beach, FL	Little Rock--North Little Rock, AR
Providence-Fall River-Pawtucket, MA/RI	Kansas City, MO-KS
Baltimore, MD	Lubbock, TX
Highest share of mobile workers	Lowest share of mobile workers
Las Vegas, NV	Buffalo-Niagara Falls, NY
Reno, NV	Pittsburgh, PA
Fort Myers-Cape Coral, FL	Syracuse, NY
West Palm Beach-Boca Raton-Delray Beach, FL	Peoria, IL
Phoenix, AZ	Toledo, OH/MI
Fort Lauderdale-Hollywood-Pompano Beach, FL	Akron, OH
Orlando, FL	Rochester, NY
Colorado Springs, CO	Lansing-E. Lansing, MI
Melbourne-Titusville-Cocoa-Palm Bay, FL	Albany-Schenectady-Troy, NY
Tampa-St. Petersburg-Clearwater, FL	Harrisburg-Lebanon--Carlisle, PA

City-specific productivity levels and based on the 2007 estimates. Mobile workers include natives who have left their birthplaces and immigrants who have at least 10,000 previous immigrants from the same country group in at least 10 other cities. This includes immigrants from all country groups listed in Table A.4. except for Cuba, Korea, Southwest Asia, Western Europe, Northern Europe, and Australia & NZ.

Table A.9: City Amenities for Natives in 2007

Best amenities for high skill male natives	Worst amenities for high skill male native
Phoenix, AZ	Stamford, CT
Los Angeles-Long Beach, CA	Salinas-Sea Side-Monterey, CA
Seattle-Everett, WA	Santa Cruz, CA
Atlanta, GA	Bridgeport, CT
Dallas-Fort Worth, TX	Visalia-Tulare-Porterville, CA
Denver-Boulder, CO	Trenton, NJ
Minneapolis-St. Paul, MN	Brownsville-Harlingen-San Benito, TX
Chicago, IL	Rockford, IL
New York-Northeastern NJ	Galveston-Texas City, TX
Washington, DC/MD/VA	Atlantic City, NJ
Best amenities for high skill female native	Worst amenities for high skill female native
Phoenix, AZ	Salinas-Sea Side-Monterey, CA
Los Angeles-Long Beach, CA	Brownsville-Harlingen-San Benito, TX
Atlanta, GA	Visalia-Tulare-Porterville, CA
Seattle-Everett, WA	Santa Cruz, CA
New York-Northeastern NJ	Stamford, CT
Chicago, IL	Rockford, IL
Dallas-Fort Worth, TX	Galveston-Texas City, TX
Boston, MA-NH	Lubbock, TX
Denver-Boulder, CO	Modesto, CA
Minneapolis-St. Paul, MN	Trenton, NJ
Best amenities for low skill male native	Worst amenities for low skill male native
Phoenix, AZ	Santa Cruz, CA
Las Vegas, NV	Salinas-Sea Side-Monterey, CA
Los Angeles-Long Beach, CA	Stamford, CT
Tampa-St. Petersburg-Clearwater, FL	Santa Barbara-Santa Maria-Lompoc, CA
Atlanta, GA	Galveston-Texas City, TX
New York-Northeastern NJ	Brownsville-Harlingen-San Benito, TX
Seattle-Everett, WA	Corpus Christi, TX
Denver-Boulder, CO	Ann Arbor, MI
Dallas-Fort Worth, TX	Visalia-Tulare-Porterville, CA
Salt Lake City-Ogden, UT	Santa Rosa-Petaluma, CA
Best amenities for low skill female native	Worst amenities for low skill female natives
Phoenix, AZ	Santa Cruz, CA
Las Vegas, NV	Salinas-Sea Side-Monterey, CA
Atlanta, GA	Santa Barbara-Santa Maria-Lompoc, CA
New York-Northeastern NJ	Visalia-Tulare-Porterville, CA
Tampa-St. Petersburg-Clearwater, FL	Galveston-Texas City, TX
Los Angeles-Long Beach, CA	Stamford, CT
Detroit, MI	Santa Rosa-Petaluma, CA
Chicago, IL	Kileen-Temple, TX
Dallas-Fort Worth, TX	Brownsville-Harlingen-San Benito, TX
Seattle-Everett, WA	Worcester, MA

Table A.10: City Amenities for Immigrants in 2007

Best amenities for high skill male immigrant	Worst amenities for high skill male immigrant
New York-Northeastern NJ	Toledo, OH/MI
Los Angeles-Long Beach, CA	Peoria, IL
Chicago, IL	Lubbock, TX
Washington, DC/MD/VA	Des Moines, IA
Miami-Hialeah, FL	Fayetteville, NC
Riverside-San Bernardino,CA	Syracuse, NY
San Francisco-Oakland-Vallejo, CA	Stamford, CT
Fort Lauderdale-Hollywood-Pompano Beach, FL	Little Rock--North Little Rock, AR
Atlanta, GA	Akron, OH
Dallas-Fort Worth, TX	Eugene-Springfield, OR
Best amenities for high skill female immigrant	**Worst amenities for high skill female immigrant**
New York-Northeastern NJ	Little Rock--North Little Rock, AR
Los Angeles-Long Beach, CA	Salem, OR
Miami-Hialeah, FL	Lubbock, TX
Chicago, IL	Peoria, IL
Washington, DC/MD/VA	Akron, OH
San Francisco-Oakland-Vallejo, CA	Toledo, OH/MI
Fort Lauderdale-Hollywood-Pompano Beach, FL	Eugene-Springfield, OR
Boston, MA-NH	Des Moines, IA
San Diego, CA	Augusta-Aiken, GA-SC
Orlando, FL	Corpus Christi, TX
Best amenities for low skill male immigrant	**Worst amenities for low skill male immigrant**
New York-Northeastern NJ	Peoria, IL
Dallas-Fort Worth, TX	Pittsburgh, PA
Houston-Brazoria, TX	Olympia, WA
Chicago, IL	Akron, OH
Phoenix, AZ	Spokane, WA
Los Angeles-Long Beach, CA	Buffalo-Niagara Falls, NY
Miami-Hialeah, FL	Toledo, OH/MI
San Francisco-Oakland-Vallejo, CA	Lansing-E. Lansing, MI
Atlanta, GA	Ann Arbor, MI
Riverside-San Bernardino,CA	Fayetteville, NC
Best amenities for low skill female immigrant	**Worst amenities for low skill female immigrant**
New York-Northeastern NJ	Peoria, IL
Houston-Brazoria, TX	Lansing-E. Lansing, MI
Chicago, IL	Ann Arbor, MI
Miami-Hialeah, FL	Olympia, WA
Dallas-Fort Worth, TX	Lubbock, TX
Los Angeles-Long Beach, CA	Corpus Christi, TX
Riverside-San Bernardino,CA	Eugene-Springfield, OR
Washington, DC/MD/VA	Akron, OH
San Francisco-Oakland-Vallejo, CA	Buffalo-Niagara Falls, NY
San Diego, CA	Fort Wayne, IN

Table A.11: Wages: Increase in High Skill Immigrants using National Labor Demand Estimates

	Gateway cities				Other cities			
	△ annual wage Fixed migration		△ annual wage Free migration		△ annual wage Fixed migration		△ annual wage Free migration	
	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
High-skill male native	-1,738	-1.5	-1,144	-1.0	-469	-0.6	-527	-0.7
High-skill female native	-1,187	-1.5	-805	-1.0	-328	-0.6	-373	-0.7
Low-skill male native	2,426	4.6	1,679	3.2	508	1.2	590	1.4
Low-skill female native	1,981	4.6	1,370	3.2	417	1.2	479	1.4
High-skill male immigrant	-1,962	-2.3	-1,494	-1.7	-1,109	-1.5	-1,094	-1.5
High-skill female immigrant	-1,428	-2.3	-1,065	-1.7	-842	-1.5	-832	-1.5
Low-skill male immigrant	1,686	4.9	1,166	3.4	656	2.1	612	1.9
Low-skill female immigrant	1,482	4.9	1,025	3.4	561	2.1	524	1.9
Housing rents	1,335	12.0	939	8.4	230	2.6	231	2.7

Gateway cities: Fort Lauderdale, Miami, New York, San Francisco and San Jose. Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. Fixed-migration change measures the difference between the initial wages and the wages when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table A.12: Welfare: Increase in High Skill Immigrants using National Labor Demand Estimates

	△ ave. utility									
	Fixed migration		Free migration							
	all workers		all workers		movers		forced stayers		stayers	
	△$	△%	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gateway cities:										
High-skill male native	-5,301	-4.6	-3,736	-3.3	-2,898	-2.6	-4,015	-3.6	-3,760	-3.3
High-skill female native	-3,606	-4.7	-2,567	-3.3	-1,933	-2.6	-2,859	-3.9	-2,577	-3.3
Low-skill male native	721	1.4	445	0.8	.	.	.	.	445	0.8
Low-skill female native	585	1.4	361	0.8	198	0.4	164	0.3	361	0.8
High-skill male immigrant	-5,131	-5.9	-3,738	-4.3	-3,093	-3.6	-4,104	-4.9	-3,786	-4.3
High-skill female immigrant	-3,723	-5.9	-2,696	-4.3	-2,190	-3.6	-2,933	-4.8	-2,730	-4.3
Low-skill male immigrant	251	0.7	145	0.4	142	0.4	11	0.0	145	0.4
Low-skill female immigrant	212	0.7	125	0.4	109	0.4	26	0.1	125	0.4
Other cities:										
High-skill male native	-1,393	-1.6	-1,424	-1.6	-1,667	-1.8	-2,229	-2.3	-1,422	-1.6
High-skill female native	-957	-1.5	-986	-1.6	-1,140	-1.7	-1,534	-2.3	-985	-1.6
Low-skill male native	303	0.7	334	0.8	349	0.8	252	0.6	334	0.8
Low-skill female native	252	0.7	278	0.8	282	0.8	202	0.6	278	0.8
High-skill male immigrant	-1,975	-2.6	-1,948	-2.6	-2,298	-3.0	-2,926	-3.9	-1,941	-2.6
High-skill female immigrant	-1,495	-2.6	-1,475	-2.6	-1,796	-3.1	-2,270	-3.9	-1,468	-2.6
Low-skill male immigrant	150	0.5	168	0.6	190	0.6	120	0.4	168	0.6
Low-skill female immigrant	122	0.5	141	0.5	149	0.6	76	0.3	141	0.5
Ave. loss/gains without rental income	-756	-0.8	-677	-0.7	-1,838	-2.3	-2,469	-3.1	-669	-0.7
Welfare with rental income										
High-skill native	-154	1.6	-74	1.6	-477	1.0	-1,127	0.3	-71	1.6
Low-skill native	683	4.0	696	4.0	696	4.0	608	3.7	696	4.0
High-skill immigrant	-1,669	-2.4	-1,286	-1.9	-1,540	-2.2	-2,301	-3.3	-1,278	-1.9
Low-skill immigrant	321	3.7	315	3.6	313	3.1	230	2.8	315	3.6
Ave. loss/gains with rental income	46	2.3	125	2.3	-850	-0.2	-1,481	-1.0	132	2.3

The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Changes in average utility reported in 2015 annual wage dollars. Forced stayer's change in utility measures the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move. Net loss/gains weighted by population share of each group. See text for more details.

Table A.13: Wages: Increase in the Stock of Immigrants using National Labor Demand Estimates

	Gateway cities				Other cities			
	△ annual wage Fixed migration		△ annual wage Free migration		△ annual wage Fixed migration		△ annual wage Free migration	
	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
High-skill male native	574	0.5	580	0.5	172	0.2	161	0.2
High-skill female native	392	0.5	391	0.5	115	0.2	107	0.2
Low-skill male native	-78	-0.2	-90	-0.2	-32	-0.1	-20	0.0
Low-skill female native	-100	-0.2	-125	-0.3	-43	-0.1	-31	-0.1
High-skill male immigrant	151	0.2	185	0.2	-21	0.0	-52	-0.1
High-skill female immigrant	116	0.2	139	0.2	-17	0.0	-40	-0.1
Low-skill male immigrant	-575	-1.7	-578	-1.7	-561	-1.8	-548	-1.7
Low-skill female immigrant	-514	-1.8	-508	-1.8	-492	-1.8	-501	-1.9
Housing rents	787	7.6	653	6.2	158	1.8	153	1.8

Gateway cities: Los Angeles, Miami, New York, Salinas-Sea and San Jose. Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. Fixed-migration change measures the difference between the initial wages and the wages when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table A.14: Welfare: Increase in the Stock of Immigrants using National Labor Demand Estimates

	△ ave. utility									
	Fixed migration		Free migration							
	all workers		all workers		movers		forced stayers		stayers	
	△\$	△%	△\$	△%	△\$	△%	△\$	△%	△\$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gateway cities:										
High-skill male native	-1,701	-1.5	-1,373	-1.2	-915	-0.8	-1,426	-1.3	-1,380	-1.2
High-skill female native	-1,173	-1.6	-951	-1.3	-625	-0.9	-983	-1.4	-955	-1.3
Low-skill male native	-1,096	-2.2	-951	-1.9	-598	-1.2	-989	-1.9	-956	-1.9
Low-skill female native	-948	-2.2	-840	-2.0	-519	-1.2	-871	-2.0	-845	-2.0
High-skill male immigrant	-1,872	-2.3	-1,489	-1.8	-1,105	-1.4	-1,584	-2.0	-1,502	-1.8
High-skill female immigrant	-1,371	-2.3	-1,095	-1.8	-803	-1.4	-1,151	-2.0	-1,105	-1.8
Low-skill male immigrant	-1,398	-4.1	-1,262	-3.7	-1,015	-3.0	-1,284	-3.8	-1,266	-3.7
Low-skill female immigrant	-1,253	-4.2	-1,118	-3.8	-913	-3.2	-1,122	-3.9	-1,125	-3.8
Other cities:										
High-skill male native	-349	-0.4	-344	-0.4	-436	-0.5	-676	-0.7	-344	-0.4
High-skill female native	-240	-0.4	-239	-0.4	-304	-0.4	-503	-0.7	-239	-0.4
Low-skill male native	-314	-0.7	-285	-0.6	-282	-0.6	-460	-1.0	-285	-0.6
Low-skill female native	-284	-0.8	-252	-0.7	-291	-0.8	-427	-1.1	-252	-0.7
High-skill male immigrant	-695	-0.9	-675	-0.9	-905	-1.1	-1,203	-1.4	-674	-0.9
High-skill female immigrant	-529	-0.9	-510	-0.9	-727	-1.2	-983	-1.6	-508	-0.9
Low-skill male immigrant	-750	-2.4	-747	-2.4	-928	-2.7	-1,110	-3.3	-747	-2.4
Low-skill female immigrant	-657	-2.5	-676	-2.5	-763	-2.7	-904	-3.2	-675	-2.5
Ave. loss/gains without rental income	-484	-1.0	-445	-0.9	-676	-1.3	-960	-1.8	-444	-0.9
Welfare with rental income										
High-skill native	496	1.9	525	1.9	366	1.6	61	1.3	525	1.9
Low-skill native	-84	1.4	-47	1.5	-108	1.4	-333	0.9	-47	1.5
High-skill immigrant	-332	-0.5	-208	-0.3	-297	-0.5	-676	-1.0	-206	-0.3
Low-skill immigrant	-737	-0.7	-712	-0.7	-797	-1.1	-999	-1.8	-711	-0.7
Ave. loss/gains with rental income	62	1.2	101	1.3	-167	0.4	-452	-0.1	102	1.3

The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Changes in average utility reported in 2015 annual wage dollars. Forced stayer's change in utility measures the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move. Net loss/gains weighted by population share of each group. See text for more details.

Table A.15: Wages: Increase in High Skill Immigrants using Different CES Order

	Gateway cities				Other cities			
	△ annual wage Fixed migration		△ annual wage Free migration		△ annual wage Fixed migration		△ annual wage Free migration	
	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
High-skill male native	209	0.2	412	0.3	-78	-0.1	-95	-0.1
High-skill female native	271	0.3	250	0.3	44	0.1	43	0.1
Low-skill male native	2,460	4.6	2,197	4.1	560	1.3	598	1.4
Low-skill female native	1,928	4.6	1,756	4.2	440	1.3	465	1.4
High-skill male immigrant	-4,468	-5.2	-4,236	-4.9	-4,126	-5.4	-4,217	-5.5
High-skill female immigrant	-3,228	-5.0	-3,098	-4.8	-3,032	-5.2	-3,125	-5.4
Low-skill male immigrant	1,690	4.8	1,494	4.2	679	2.2	668	2.2
Low-skill female immigrant	1,421	4.8	1,296	4.4	560	2.2	548	2.2
Housing rents	1,318	11.8	1,082	9.6	226	2.6	227	2.7

Gateway cities: Fort Lauderdale, Miami, New York, San Francisco and San Jose. Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. Fixed-migration change measures the difference between the initial wages and the wages when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table A.16: Welfare: Increase in High Skill Immigrants using Different CES Order

	△ ave. utility									
	Fixed migration		Free migration							
	all workers		all workers		movers		forced stayers		stayers	
	△$	△%	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gateway cities:										
High-skill male native	-3,375	-3.0	-2,613	-2.3	-1,938	-1.8	-2,805	-2.6	-2,632	-2.3
High-skill female native	-2,220	-2.8	-1,844	-2.3	-1,229	-1.6	-2,111	-2.8	-1,854	-2.4
Low-skill male native	747	1.4	746	1.4	.	.	.	.	746	1.4
Low-skill female native	582	1.4	611	1.5	.	.	.	.	611	1.5
High-skill male immigrant	-7,531	-8.7	-6,785	-7.8	-6,204	-7.3	-6,855	-8.1	-6,815	-7.8
High-skill female immigrant	-5,488	-8.6	-4,971	-7.7	-4,501	-7.2	-5,028	-8.0	-4,995	-7.7
Low-skill male immigrant	261	0.7	307	0.9	203	0.6	114	0.3	308	0.9
Low-skill female immigrant	211	0.7	289	1.0	268	0.9	197	0.7	289	1.0
Other cities:										
High-skill male native	-859	-1.0	-834	-0.9	-1,003	-1.1	-1,446	-1.5	-833	-0.9
High-skill female native	-476	-0.7	-482	-0.8	-523	-0.8	-973	-1.4	-482	-0.8
Low-skill male native	381	0.9	398	0.9	431	1.0	295	0.7	398	0.9
Low-skill female native	303	0.9	309	0.9	337	1.0	237	0.7	309	0.9
High-skill male immigrant	-4,927	-6.5	-5,028	-6.7	-5,264	-6.9	-5,676	-7.4	-5,026	-6.7
High-skill female immigrant	-3,661	-6.4	-3,749	-6.6	-4,062	-6.8	-4,450	-7.5	-3,745	-6.5
Low-skill male immigrant	195	0.6	202	0.7	247	0.8	142	0.5	202	0.7
Low-skill female immigrant	159	0.6	160	0.6	195	0.8	125	0.5	159	0.6
Ave. loss/gains without rental income	-727	-0.8	-686	-0.7	-2,386	-3.0	-2,843	-3.7	-676	-0.7
Welfare with rental income										
High-skill native	432	2.4	488	2.4	163	1.8	-422	1.1	489	2.4
Low-skill native	740	4.1	753	4.1	764	4.2	644	3.9	753	4.1
High-skill immigrant	-4,098	-5.9	-3,988	-5.8	-4,273	-6.0	-4,793	-6.7	-3,982	-5.8
Low-skill immigrant	354	3.7	371	3.7	376	3.4	292	3.1	371	3.7
Ave. loss/gains with rental income	62	2.3	103	2.3	-1,467	-0.8	-1,924	-1.4	113	2.3

The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Changes in average utility reported in 2015 annual wage dollars. Forced stayer's change in utility measures the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move. Net loss/gains weighted by population share of each group. See text for more details.

Table A.17: Wages: Increase in the Stock of Immigrants using Different CES Order

	Gateway cities				Other cities			
	△ annual wage Fixed migration		△ annual wage Free migration		△ annual wage Fixed migration		△ annual wage Free migration	
	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
High-skill male native	1,356	1.2	1,261	1.1	321	0.4	327	0.4
High-skill female native	1,008	1.3	888	1.1	268	0.4	278	0.5
Low-skill male native	-270	-0.5	-236	-0.5	-60	-0.1	-54	-0.1
Low-skill female native	-75	-0.2	67	0.2	26	0.1	20	0.1
High-skill male immigrant	-1,101	-1.3	-1,077	-1.3	-1,538	-2.0	-1,621	-2.1
High-skill female immigrant	-782	-1.2	-818	-1.3	-1,109	-1.9	-1,173	-2.0
Low-skill male immigrant	-503	-1.5	-493	-1.5	-421	-1.4	-406	-1.3
Low-skill female immigrant	-319	-1.2	-200	-0.7	-250	-1.0	-252	-1.0
Housing rents	782	7.5	666	6.3	156	1.8	154	1.8

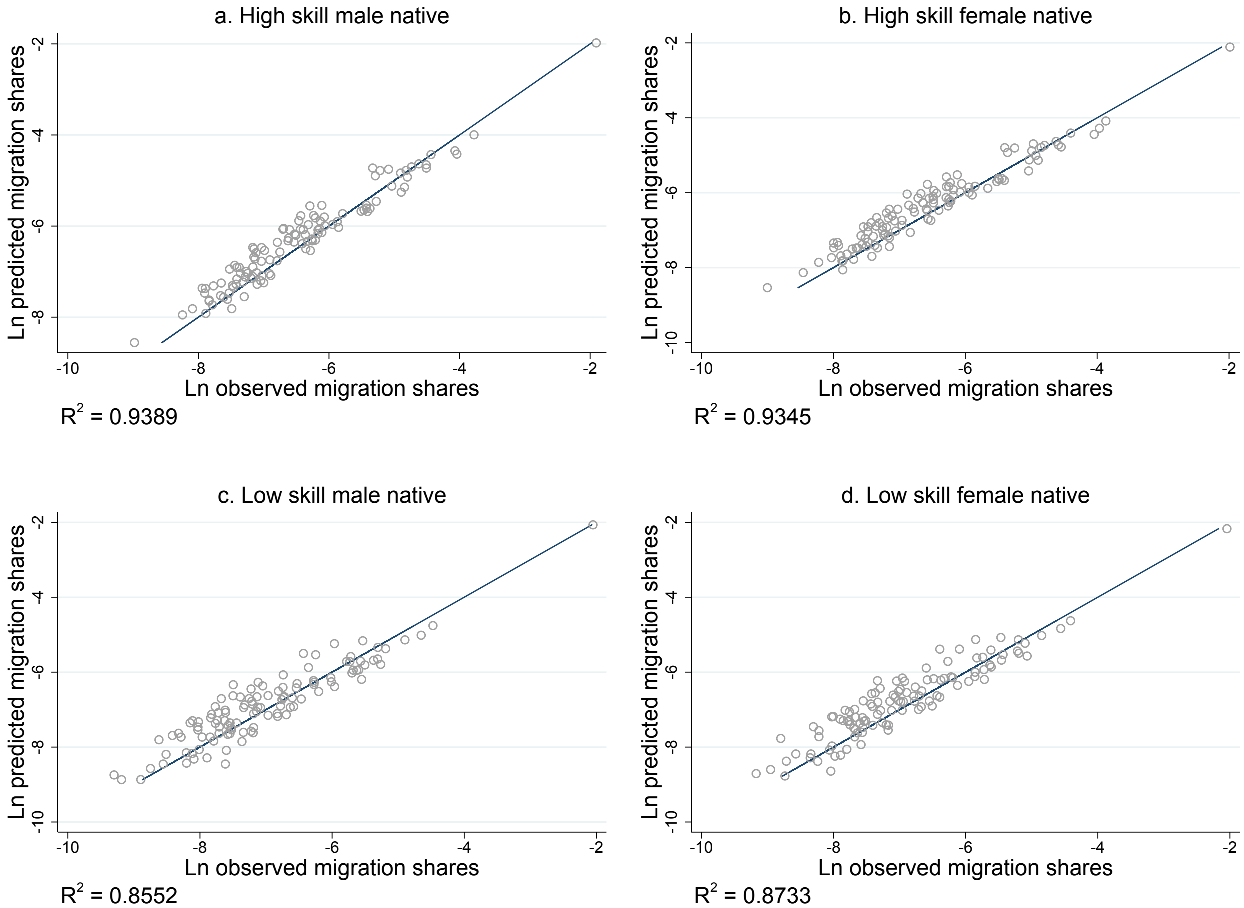
Gateway cities: Los Angeles, Miami, New York, Salinas-Sea and San Jose. Average wage of each group weighted by the number of workers in each city. Annual wages in 2015 dollars. Fixed-migration change measures the difference between the initial wages and the wages when natives and immigrants' locations are held fixed. Free-migration change measures the difference between the initial wages and the wages after all workers simultaneously choose locations.

Table A.18: Welfare: Increase in the Stock of Immigrants using Different CES Order

	△ ave. utility									
	Fixed migration		Free migration							
	all workers		all workers		movers		forced stayers		stayers	
	△$	△%	△$	△%	△$	△%	△$	△%	△$	△%
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gateway cities:										
High-skill male native	-938	-0.8	-730	-0.7	-554	-0.5	-948	-0.8	-732	-0.7
High-skill female native	-604	-0.8	-514	-0.7	-339	-0.5	-846	-1.3	-516	-0.7
Low-skill male native	-1,271	-2.5	-1,104	-2.2	-731	-1.5	-1,140	-2.4	-1,112	-2.2
Low-skill female native	-878	-2.2	-635	-1.5	-481	-1.2	-701	-1.7	-637	-1.6
High-skill male immigrant	-3,104	-3.7	-2,796	-3.3	-2,638	-3.2	-2,906	-3.5	-2,799	-3.3
High-skill female immigrant	-2,285	-3.7	-2,100	-3.3	-1,930	-3.2	-2,147	-3.6	-2,104	-3.4
Low-skill male immigrant	-1,314	-3.8	-1,194	-3.5	-881	-2.6	-1,234	-3.7	-1,201	-3.5
Low-skill female immigrant	-1,025	-3.6	-797	-2.8	-630	-2.2	-815	-2.8	-803	-2.8
Other cities:										
High-skill male native	-142	-0.2	-133	-0.1	-243	-0.2	-418	-0.4	-133	-0.1
High-skill female native	-45	-0.1	-43	-0.1	-84	-0.1	-211	-0.3	-43	-0.1
Low-skill male native	-362	-0.8	-341	-0.8	-371	-0.8	-546	-1.2	-341	-0.8
Low-skill female native	-184	-0.5	-183	-0.5	-230	-0.6	-345	-0.9	-182	-0.5
High-skill male immigrant	-2,164	-2.8	-2,217	-2.9	-2,554	-3.0	-2,810	-3.3	-2215	-2.9
High-skill female immigrant	-1,600	-2.8	-1,642	-2.8	-1,839	-3.0	-2,037	-3.3	-1641	-2.8
Low-skill male immigrant	-598	-1.9	-595	-1.9	-785	-2.3	-998	-2.9	-594	-1.9
Low-skill female immigrant	-437	-1.7	-442	-1.7	-580	-2.1	-715	-2.5	-441	-1.7
Ave. loss/gains without rental income	-462	-0.9	-437	-0.9	-786	-1.5	-1,010	-2.0	-435	-0.9
Welfare with rental income										
High-skill native	734	2.2	753	2.2	640	2.0	403	1.7	753	2.2
Low-skill native	-74	1.5	-50	1.5	-139	1.3	-339	0.9	-49	1.5
High-skill immigrant	-1,552	-2.2	-1,505	-2.2	-1,629	-2.3	-1,865	-2.6	-1,504	-2.2
Low-skill immigrant	-578	-0.2	-541	-0.1	-617	-0.5	-848	-1.2	-540	-0.1
Ave. loss/gains with rental income	79	1.3	105	1.3	-353	0.4	-576	-0.1	107	1.3

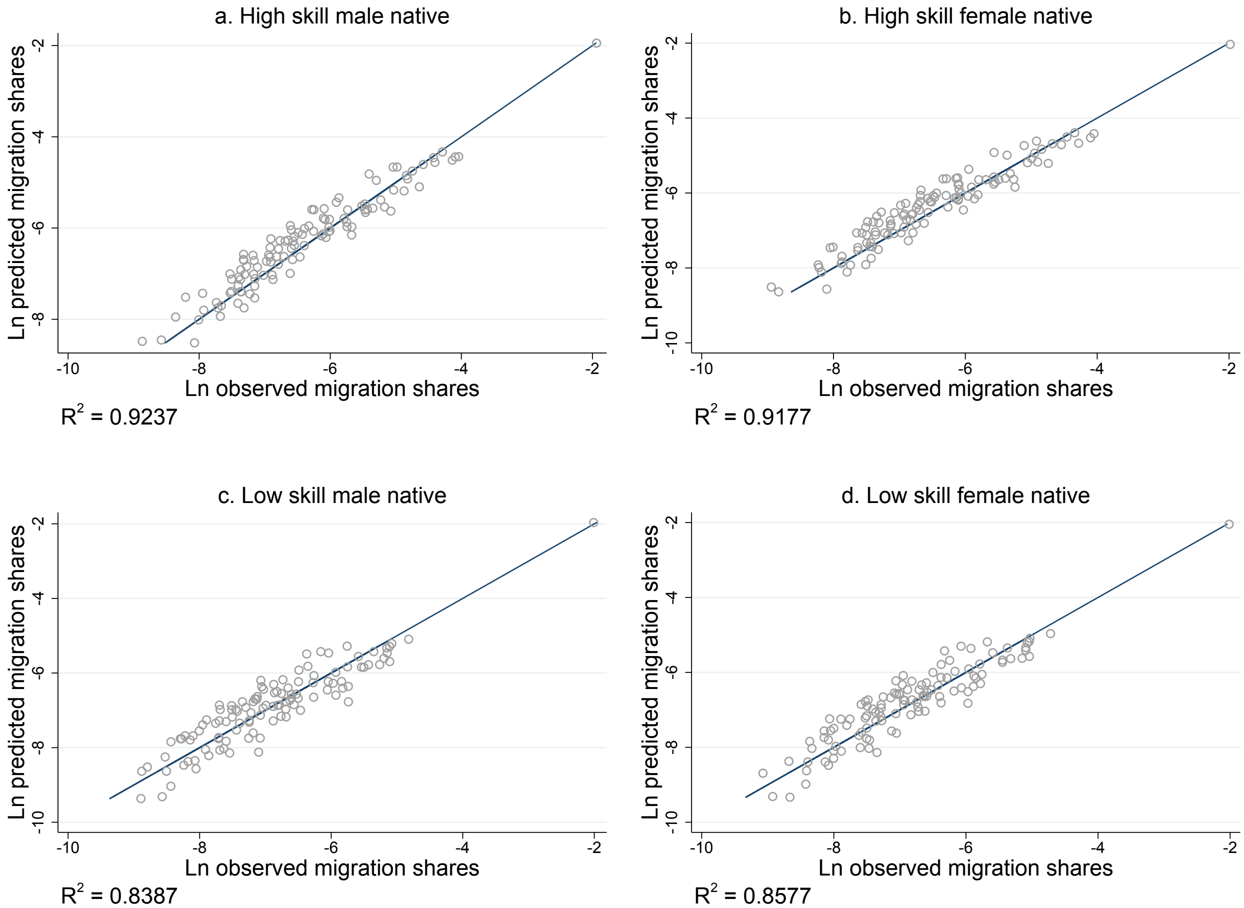
The welfare analysis is based on simulated outcomes amongst a random draw of 240,000 individuals. Changes in average utility reported in 2015 annual wage dollars. Forced stayer's change in utility measures the difference between the initial utility and the counterfactual utility that those workers who choose to move in equilibrium would have derived had they not been allowed to move. Net loss/gains weighted by population share of each group. See text for more details.

Figure A.1: Goodness of Fit: Natives in 1990



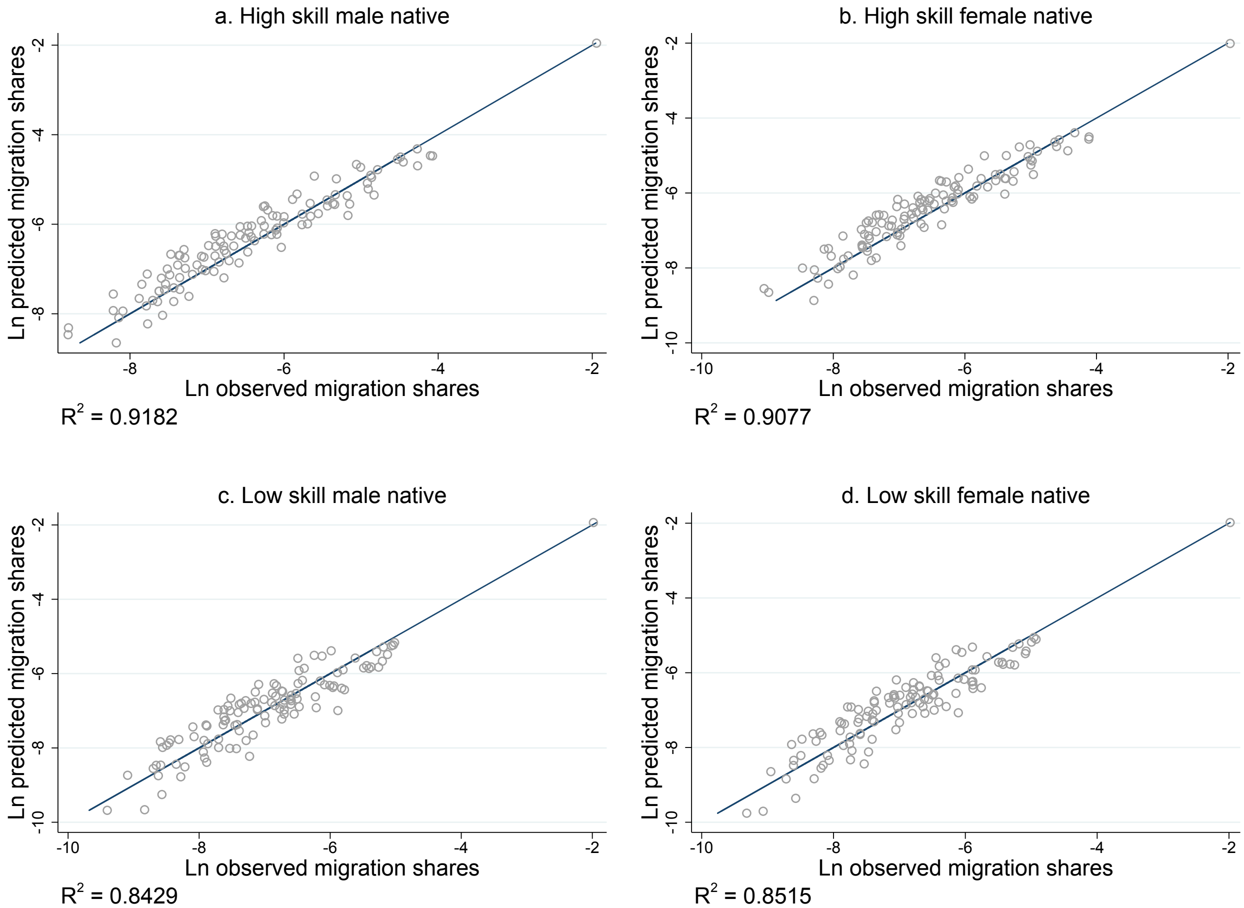
Each bubble is a metropolitan area. The y-axis represents the logarithm of the predicted share of natives who reside outside their birth states while the x-axis represents the logarithm of observed share.

Figure A.2: Goodness of Fit: Natives in 2000



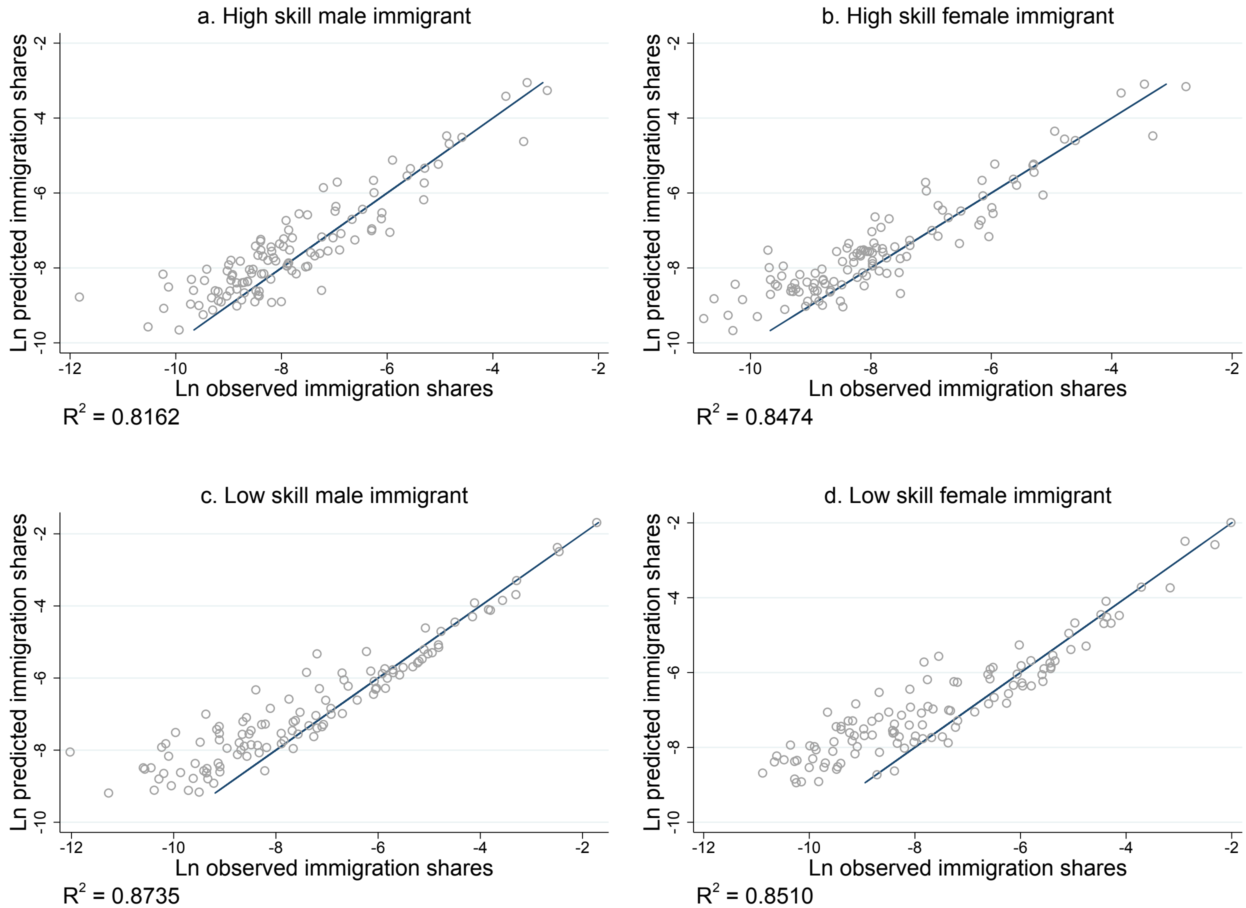
Each bubble is a metropolitan area. The y-axis represents the logarithm of the predicted share of natives who reside outside their birth states while the x-axis represents the logarithm of observed share.

Figure A.3: Goodness of Fit: Natives in 2007



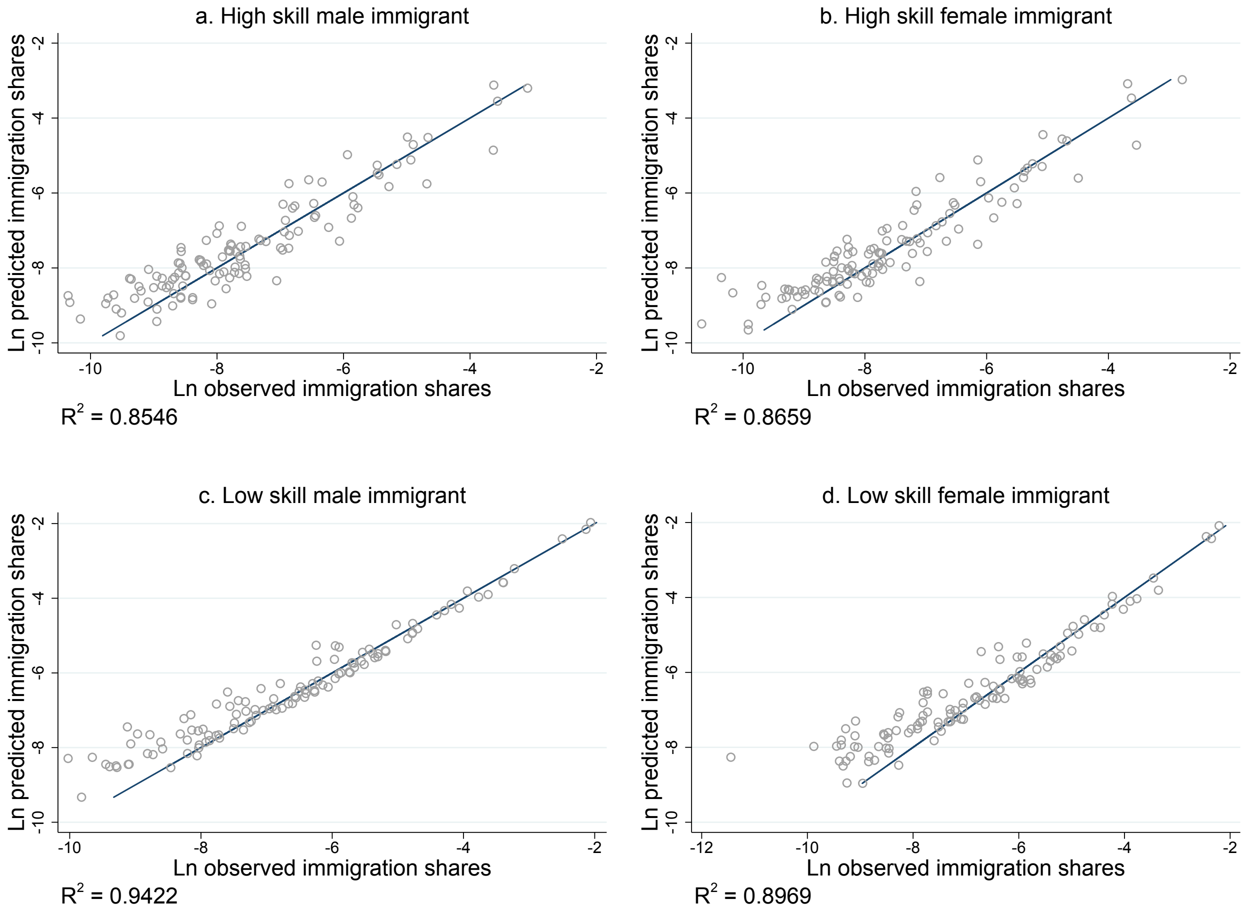
Each bubble is a metropolitan area. The y-axis represents the logarithm of the predicted share of natives who reside outside their birth states while the x-axis represents the logarithm of observed share.

Figure A.4: Goodness of Fit: Immigrants in 1990



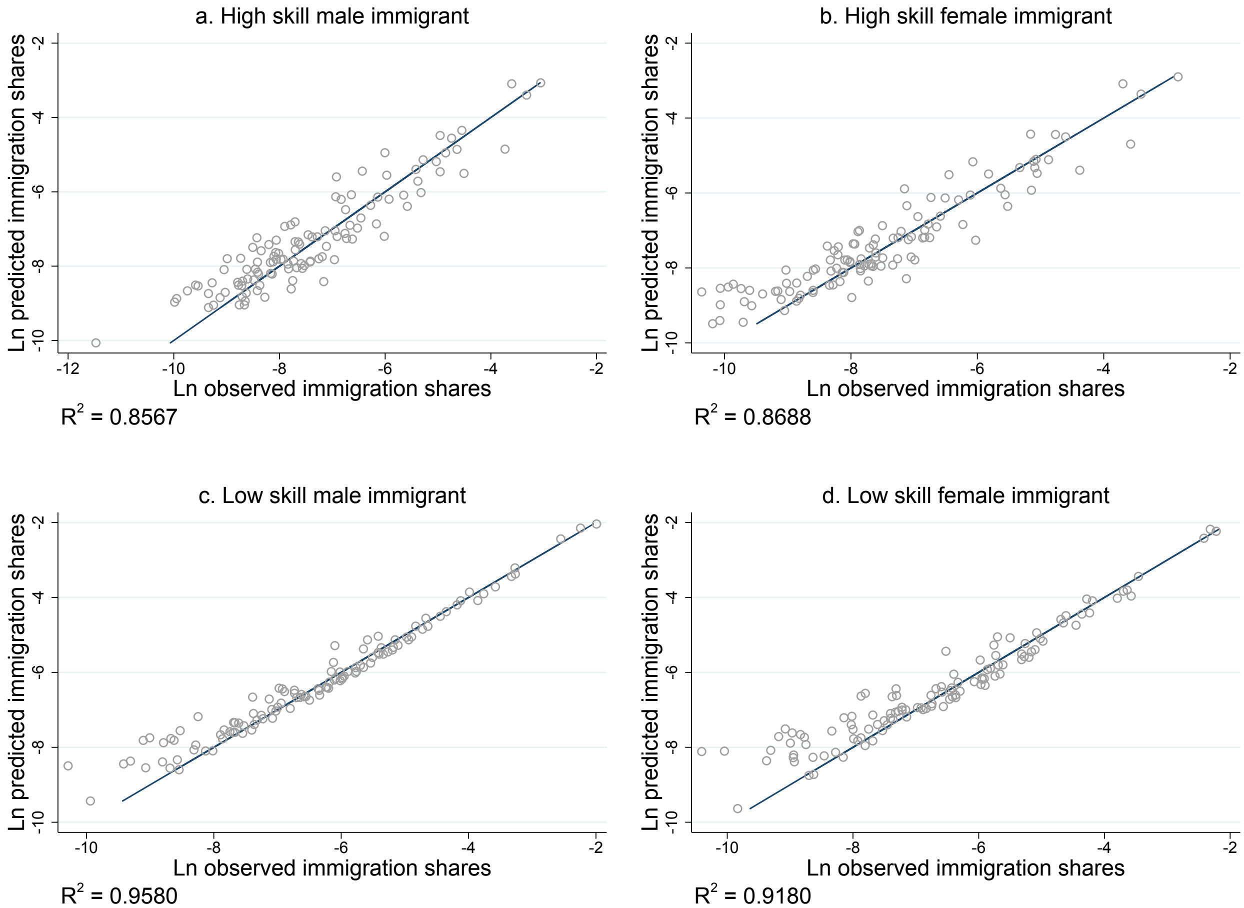
Each bubble is a metropolitan area. The y-axis represents the logarithm of the predicted share of immigrants from major sending countries: Mexico, Central America, South America and the Caribbean, while the x-axis represents the observed share.

Figure A.5: Goodness of Fit: Immigrants in 2000



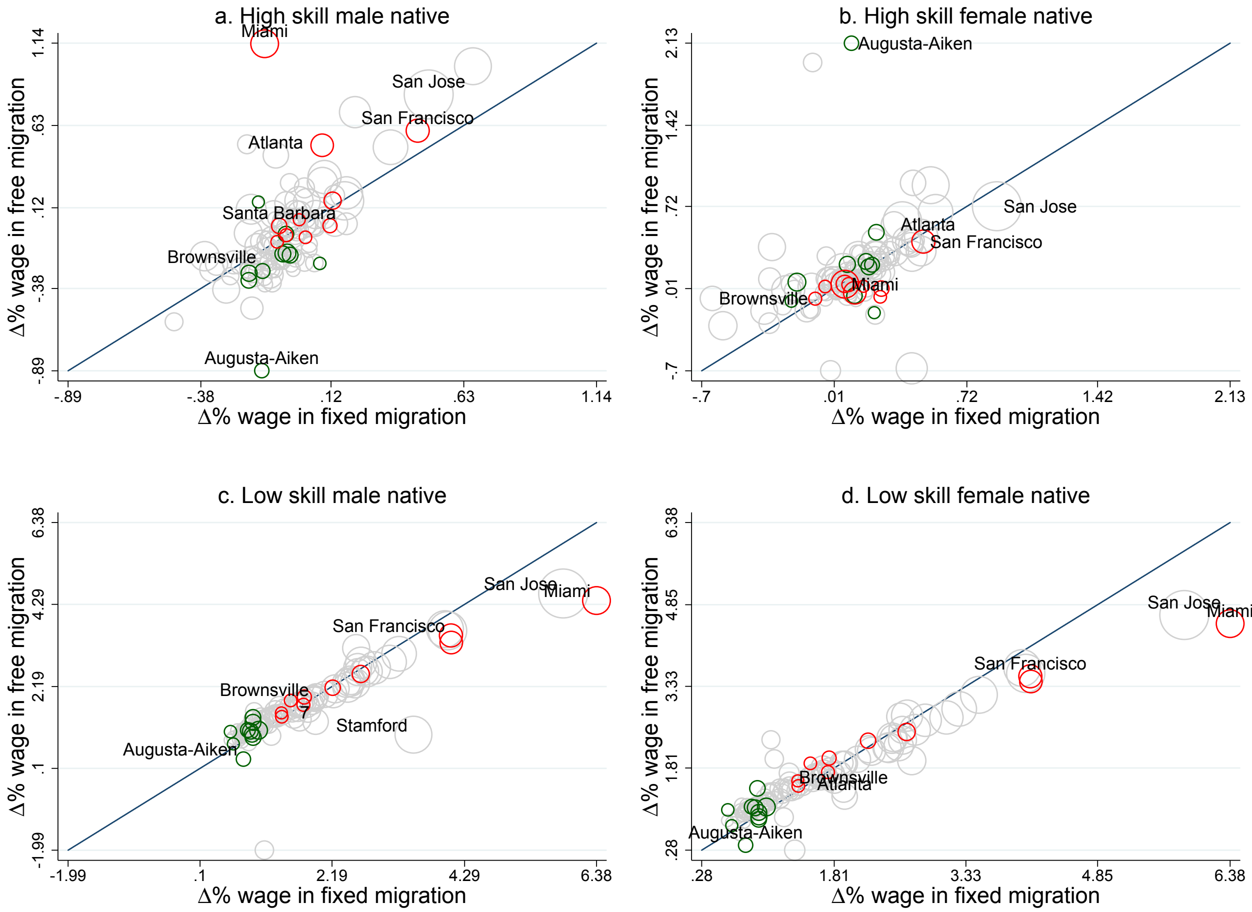
Each bubble is a metropolitan area. The y-axis represents the logarithm of the predicted share of immigrants from major sending countries: Mexico, Central America, South America and the Caribbean, while the x-axis represents the observed share.

Figure A.6: Goodness of Fit: Immigrants in 2007



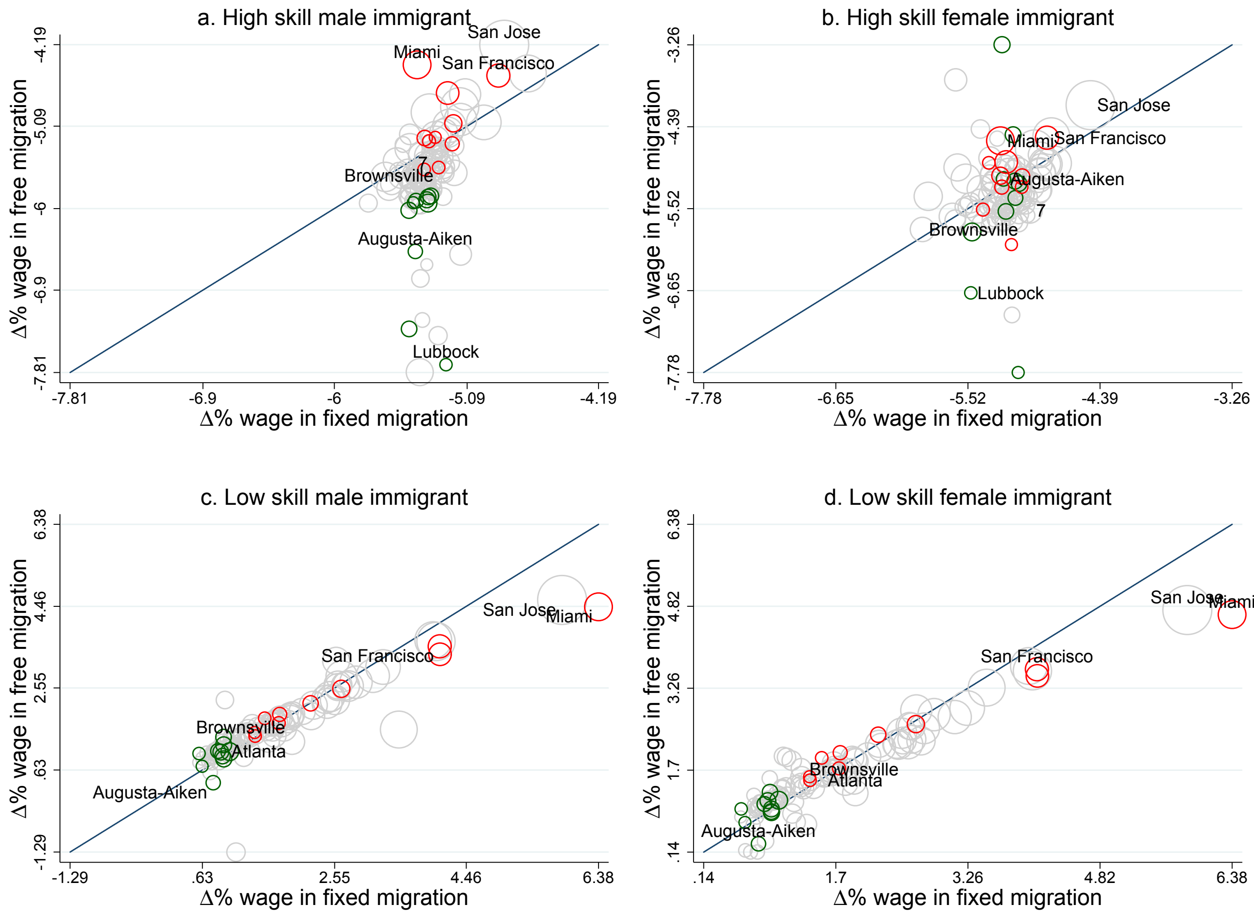
Each bubble is a metropolitan area. The y-axis represents the logarithm of the predicted share of immigrants from major sending countries: Mexico, Central America, South America and the Caribbean, while the x-axis represents the observed share.

Figure A.7: Native Wages: Increase in High Skill Immigrants



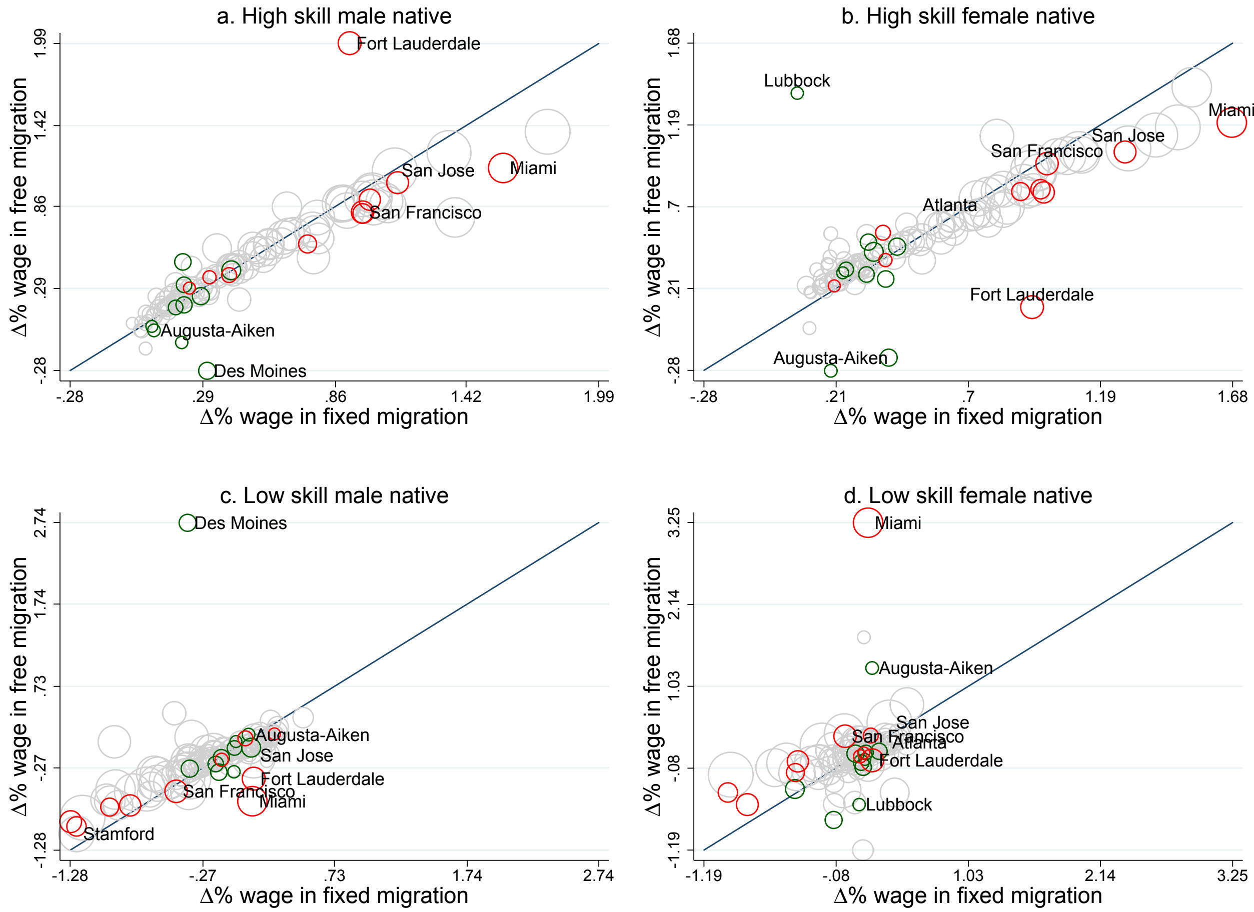
Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial wages to the fixed-migration wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply.

Figure A.8: Immigrant Wages: Increase in High Skill Immigrants



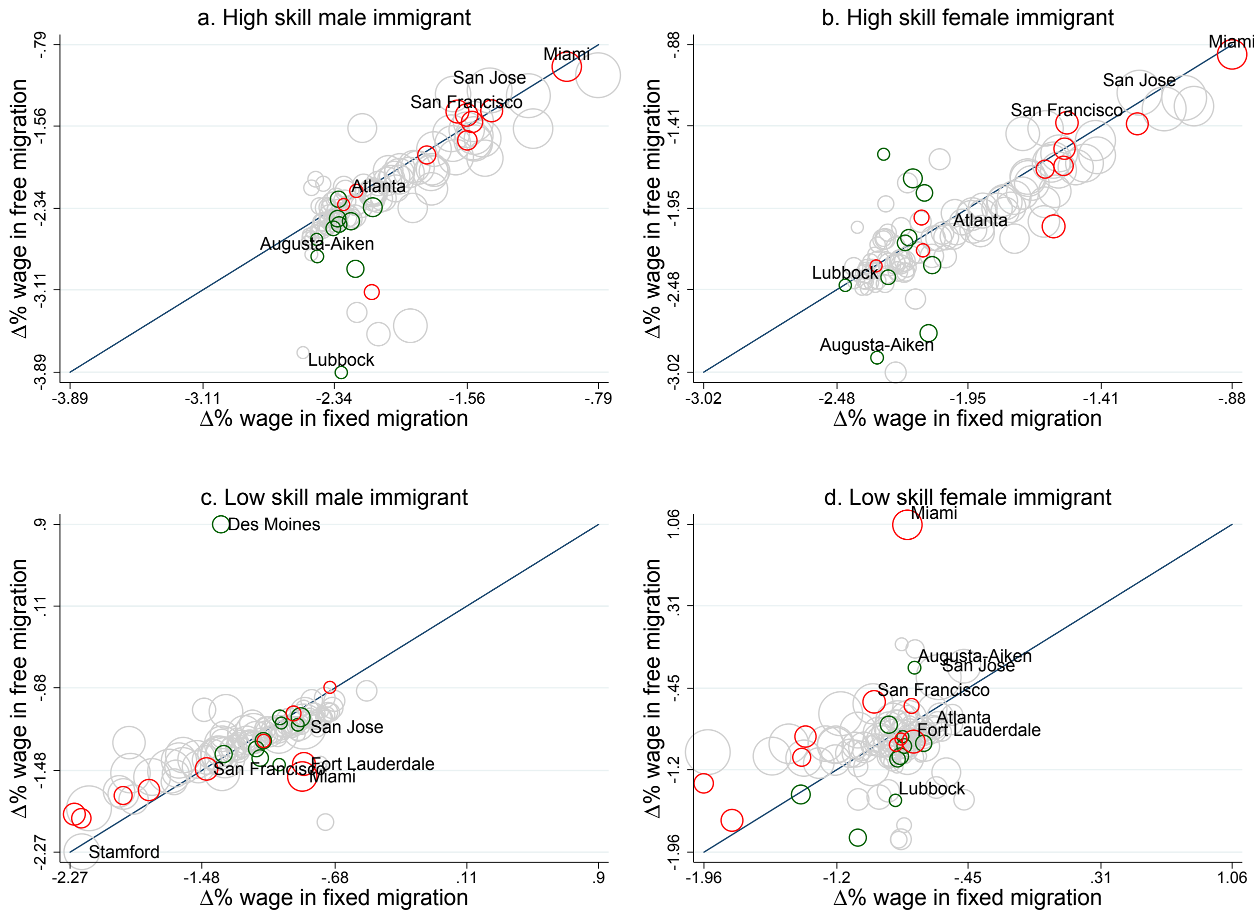
Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial wages to the fixed-migration wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply.

Figure A.9: Native Wages: Increase in the Stock of Immigrants



Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial wages to the fixed-migration wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply.

Figure A.10: Immigrant Wages: Increase in the Stock of Immigrants



Each bubble is a metropolitan area. The size of a bubble reflects the number of new immigrants as a proportion of local population in a given city. The x-axis represents the percentage change from the initial wages to the fixed-migration wages where workers are constrained to remain in their original locations. The y-axis represents the percentage change from the initial wages to the free-migration case where all workers simultaneously relocate. Red bubbles represent the ten cities with most inelastic housing supply, while green bubbles represent the ten with the least inelastic supply.