APPENDIX FOR ONLINE PUBLICATION
Immigration and Spatial Equilibrium: The Role of Expenditures in the Country of Origin

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We document that international migrants concentrate more in expensive cities – the more so, the lower the prices in their origin countries are – and consume less locally than comparable natives. We rationalize this empirical evidence by introducing a quantitative spatial equilibrium model, in which a part of immigrants' income goes towards consumption in their origin countries. Using counterfactual simulations, we show that, due to this novel consumption channel, immigrants move economic activity toward expensive, high-productivity locations. This leads to a more efficient spatial allocation of labor and, as a result, increases the aggregate output and welfare of natives.
JEL: F22, J31, J61, R11
Keywords: Immigration, location choices, spatial equilibrium

I. Empirical appendix

A. Evidence on job-finding rates and wages

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

Panel A of Figure A.3 plots the unemployment rates of immigrants, averaged from Current Population Survey (CPS) monthly data over the period 1995-2005, against city prices

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in the year 2000.[1] The relationship is flat, indicating that immigrants do not gain in terms of the probability of being employed in more expensive cities.

If the transition rates between employment and unemployment (i.e., both job-finding and separation rates) are higher in expensive cities, this might result in immigrant unemployment rates of similar magnitude. However, if immigrants care more about finding a job than about the job's duration (to establish an employment history, for instance), then they would still be drawn to larger cities. In Panel B, we therefore plot monthly immigrant job-finding rates instead of unemployment rates against city prices.[2] It shows a slightly negative relationship, suggesting that unemployment duration actually increases with the price level.

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

First, it may be that immigrants and natives within narrowly defined skill groups are imperfect substitutes. Hence, even if their concentration is demand driven, they might earn less than natives, if the labor services usually offered by immigrants as opposed to natives pay lower wages. Second, the skill sorting of natives and immigrants across cities might be different and could partly drive local wage gaps. Third, it could be that the gap in earnings between natives and immigrants varies with education, which might for instance be larger among high-skilled workers than among low-skilled workers. In this case, the higher concentration of high-skilled workers in larger cities (i.e, the sorting of skills across cities) could generate higher average wage gaps in these locations.

To control for these factors, we combine the empirical approaches of Card (2009) and Ottaviano and Peri (2012). In particular, we estimate a model in which we relate the gap in wages between natives and immigrants to their relative labor supplies in a Metropolitan Statistical Area (MSA), following Card (2009). Moreover, we group workers in skill cells based on education and experience and calculate wage and employment ratios within those cells, as in Ottaviano and Peri (2012).[3] The inclusion of skill cell fixed effects absorbs any variation in wage gaps across cities due to different sorting along the education and experience dimensions. More concretely, we estimate the following regression:

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

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

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

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

where $\hat{w}_{I,k,c,t}$ and $\hat{w}_{N,k,c,t}$ are the average composition-adjusted log wages and $L_{I,k,c,t}$ and $L_{N,k,c,t}$ the total hours worked in skill cell k and city c at time t for immigrants and natives, respectively. Since, compared to Ottaviano and Peri (2012), our data are further disaggregated at the MSA level, we opt for larger skill cells in order to have enough observations in each cell. In particular, cells are defined by two education groups (high school or less and at least some college) and four 10-year experience intervals.[4]

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

The last column of Table A.4 in online Appendix IV presents the estimate of the coefficient γ, which gives the negative inverse elasticity of substitution between natives and immigrants. For comparison, we show the estimates obtained with alternative specifications used in the literature in the first three columns.[5] In Column 4, we estimate regression (I.1) without MSA or MSA-year fixed effects. Thus, γ is identified using variation within skill cells over time and across MSAs. With this specification, we obtain a coefficient that implies an elasticity of substitution of around 20, which is the actual consensus estimate in the literature. However, after including MSA fixed effects in Column 5, the estimate becomes much smaller, implying an elasticity of 74. In our final specification with MSA-year fixed effects, the coefficient essentially becomes zero. Thus, once we account for MSA-specific time trends, we find no indication for imperfect substitutability between natives and immigrants at the local level (see also Borjas, Grogger and Hanson, 2012; Ruist, 2013).[6]

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

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

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

We report the results of estimating Equation I.2 in Table A.5, where we replicate the

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

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

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

exact same format as Table 3 using this composition-adjusted measure of wage gaps instead of the immigrant concentration. The results are a mirror image of Table 3: the gap in wages between natives and immigrants increases with the price level.

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

B. Homeownership

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

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

where "Owner" indicates whether the head of household i is a homeowner or not, Immigrant_i is a dummy indicating that household i has at least one immigrant, and X_i denotes various household characteristics, like the education level of the head of the household, marital status, the race of the head of the household, the size of the household, MSA fixed effects, occupation fixed effects, and time fixed effects. Thus, a negative β indicates that immigrants tend to rent rather than own the house in which they live, relative to comparable natives. The results are shown in Table A.9. It is apparent that immigrants are around 10 percentage points less likely to own the house in which they reside.

II. Theory appendix

A. Derivation of indirect utility

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

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

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

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

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

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

This leads to:

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

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

where:

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

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

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

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

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

B. *Derivation of housing supply equation*

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

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

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

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

FOC w.r.t. Y^T:

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

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

Now with this demand for tradables:

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

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

C. Proofs of propositions of the quantitative model

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

With this definition of what, in the context of the model, being an immigrant means, we can use Equation III.3 to obtain the following result.

PROPOSITION 1: *The immigrant concentration is given by Equation III.9, which is increasing in the local price level p_c and in immigrant-specific network amenities Z_{jc}^{Net}. It increases more steeply in p_c with lower origin prices p_j, iff $\sigma > 1$.*

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

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

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

and substitute for the different terms:

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

Taking logs, we obtain the expression above.

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

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

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

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

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

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

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

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

This concludes the proof.

D. *Comparison of housing supply equation with Hsieh and Moretti (2019)*

As shown above in Section II.B, we derive the housing supply from profit maximization of developers as a function of fixed land, the local price level, and the housing supply elasticity:

$$Y_c^H = T_c^H p_c^{\gamma_c}. \tag{II.6}$$

In contrast, the housing supply equation in Hsieh and Moretti (2019) (Equation (4) in their paper) in the notation used throughout our paper is:[7]

$$L_c = \bar{P}_c^{-\gamma_c} p_c^{\gamma_c}. \tag{II.7}$$

First, note that the second equation is stated in terms of population L_c. This is not very important since, without immigrants, the demand for housing in our model is equal to $\beta w_c / p_c L_c$ and thus proportional to population.[8]

Apart from this difference, the two equations are equivalent whenever we conduct counterfactuals that do *not* involve changing γ_c, since in both cases the constant terms are calibrated to match the data, so that $\bar{P}_c^{-\gamma_c} = T_c^H$. However, when doing counterfactuals where the value of γ_c is changed, then term $\bar{P}_c^{-\gamma_c}$ will change in (II.7), while T_c^H remains fixed in (II.6). As a consequence, the general equilibrium effects of a change in γ_c on population and, eventually, output and welfare are an order of magnitude larger when modeling the housing supply using II.7 instead of II.6. This explains why the numbers that we obtain in the first two rows of Table 7 are not directly comparable to those obtained in Hsieh and Moretti (2019).

[7] To obtain the below equation, note that Hsieh and Moretti (2019) denote the *inverse* housing supply elasticity in location i as γ_i.

[8] Ignoring immigrants and their different housing demand function, the difference between stating the equation in term of Y_c^H or L_c only comes from general equilibrium effects on the ratio w_c/p_c, which are relatively minor.

III. Figures appendix

Figure A.1. : Immigration concentration, robustness

Panel A: Immigrant concentration and MSA local price index

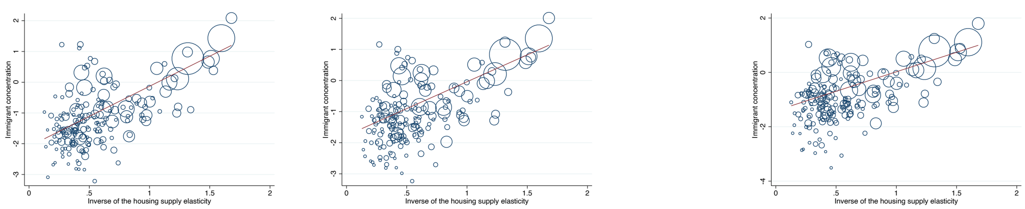
Year 1990 Year 2000 Year 2010

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

Year 1990 Year 2000 Year 2010

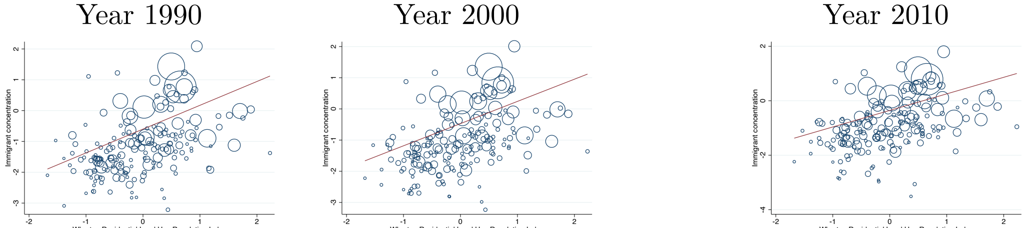
Panel C: Immigrant concentration and inverse housing supply elasticity

Year 1990 Year 2000 Year 2010



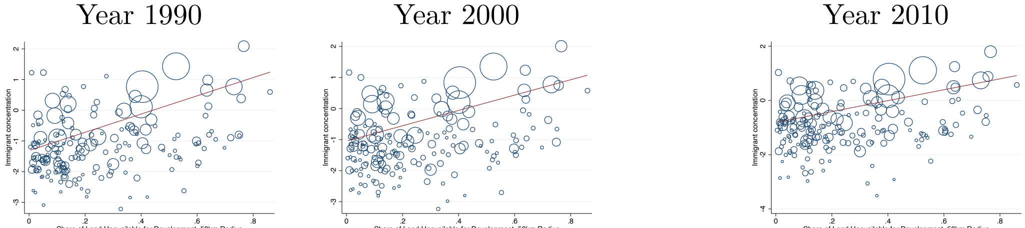
Panel D: Immigrant concentration and Wharton Residential Land Use Regulation Index

Year 1990 Year 2000 Year 2010



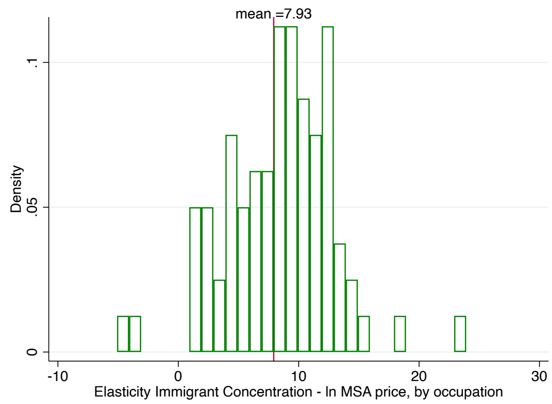
Panel E: Immigrant concentration and share sand unavailable for development

Year 1990 Year 2000 Year 2010



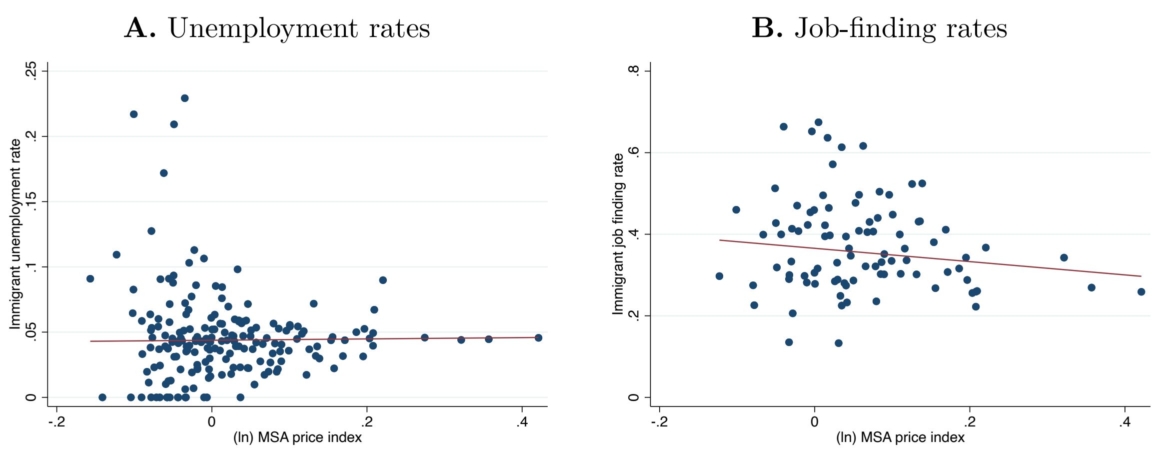
Note: This figure shows the relationship between the immigrant concentration in a Metropolitan Statistical Area (MSA) and different measures of the MSA price index. Immigrant concentration is measured as the number of immigrants in the MSA relative to all immigrants in the United States divided by the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

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



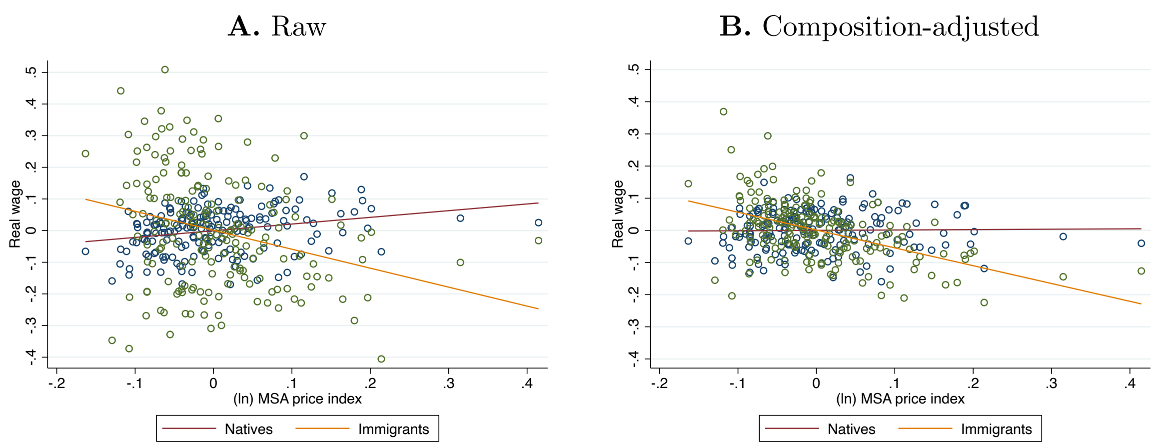
Note: This figure shows a histogram of the estimates of the elasticity of the immigrant concentration with respect to the MSA price index for 81 different aggregate occupations (which cover all the occupations recorded in Census data), controlling for population size and instrumenting the MSA price index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

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



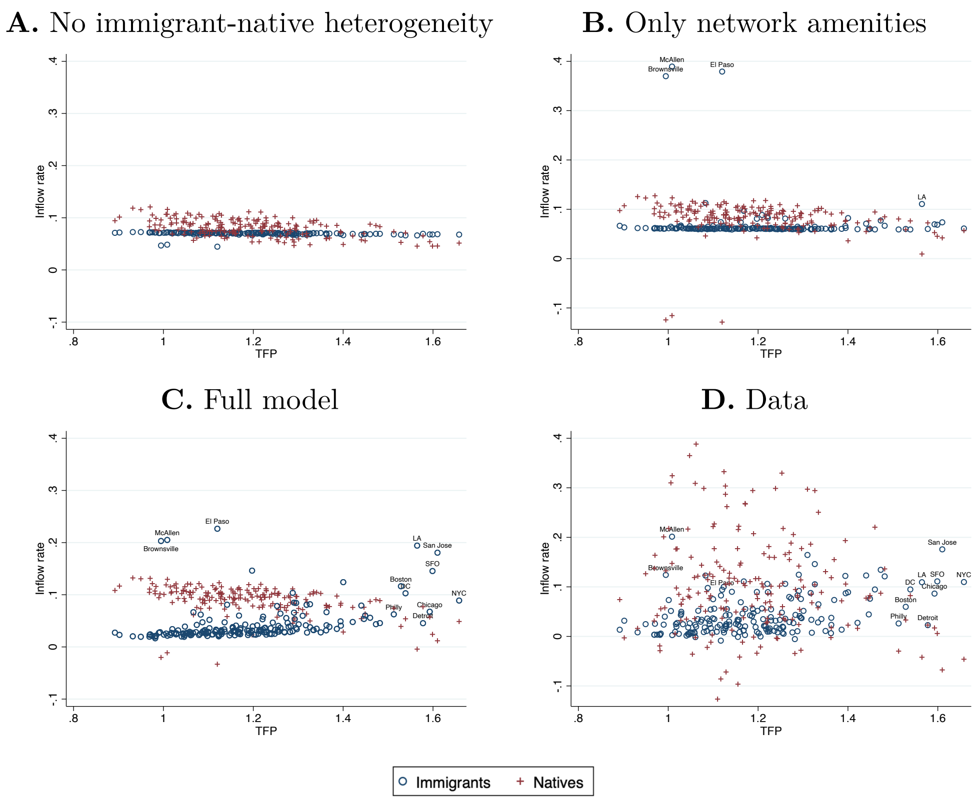
Note: This figure uses city price data from the 2000 Census and data for immigrant workers aged 25 to 59 from the CPS basic monthly files. The unemployment and job-finding rates are calculated for each city that can be matched to the Census data and are computed as the average of the variable over the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

Figure A.4. : City price, and real wages



Note: Panel A plots the average weekly wage of natives or immigrants in a city, divided by the city price. Instead of raw average weekly wages, Panel B uses the residuals from a regression of the (log) weekly wage on dummies for sex, race, marital status, education level, and experience level. Both plots show log differences to the respective sample means.

Figure A.5. : The role of immigrant consumption channel in explaining non-targeted moment II



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

IV. Tables appendix

Table A.1—: Ten highest and lowest real exchange rates vs. USD, 1990, 2000, 2010

	Highest		Lowest	
1	Norway	1.36	Vietnam	.2
2	Japan	1.34	Pakistan	.21
3	Bermuda	1.34	Lao PDR	.22
4	Denmark	1.3	Yemen	.23
5	Switzerland	1.29	Egypt	.24
6	Sweden	1.25	Sierra Leone	.24
7	Finland	1.22	Sri Lanka	.24
8	Iceland	1.11	Nepal	.25
9	United Kingdom	1.1	Indonesia	.26
10	Luxembourg	1.07	Azerbaijan	.26

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

Table A.2—: Immigrant concentration and price levels by education level

	Dep. Var.: Immigrant concentration							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
(ln) Price	6.707	7.362	6.218	4.564	7.099	8.626	8.082	5.534
	(1.343)	(0.909)	(0.659)	(0.537)	(2.848)	(2.052)	(1.553)	(1.224)
(ln) Population	0.262	0.218	0.199	0.183	0.239	0.149	0.097	0.129
	(0.093)	(0.061)	(0.048)	(0.038)	(0.177)	(0.122)	(0.094)	(0.074)
Observations	554	555	555	555	554	555	555	555
R-squared	0.520	0.681	0.713	0.728	0.519	0.676	0.694	0.718
Educ. level	<HS	HS	SC	C	<HS	HS	SC	C

Note: The dependent variable is the immigrant concentration, which is measured as the number of immigrants in the MSA relative to all immigrants in the United States divided by the number of natives in the MSA relative to all natives in the United States. The regressions use Census and ACS data for 185 MSAs for the years 1990, 2000, and 2010. <HS denotes high school dropouts, HS denotes high school graduates, SC denotes individuals with some college, and C denotes college graduates. Columns 5 to 8 instrument the price level by the housing supply elasticity estimated in Saiz (2010) as in column 8 of Table 2. All the columns include year fixed effects. Observations are weighted by MSA population. Standard errors are clustered at the MSA level.

Table A.3—: Immigration and city price levels, robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Immigrant concentration, OLS										
(ln) Price	5.687	7.059	5.812	6.220	5.692	5.715	6.320	7.448	6.551	4.631
	(0.796)	(1.201)	(0.714)	(0.985)	(0.364)	(0.825)	(1.409)	(0.976)	(0.719)	(0.571)
(ln) Population	0.227	0.248	0.205	0.266	0.190	0.227	0.284	0.237	0.207	0.167
	(0.054)	(0.081)	(0.049)	(0.072)	(0.029)	(0.058)	(0.106)	(0.068)	(0.053)	(0.041)
Observations	555	555	555	555	555	555	552	553	555	555
R-squared	0.643	0.576	0.662	0.603	0.843	0.633	0.487	0.664	0.703	0.711
B. Immigrant concentration, IV	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(ln) Price	6.585	7.412	7.735	4.560	6.543	6.282	5.684	8.238	8.396	5.409
	(1.847)	(2.624)	(1.807)	(1.975)	(0.840)	(1.866)	(2.709)	(2.158)	(1.675)	(1.242)
(ln) Population	0.177	0.228	0.099	0.357	0.143	0.195	0.320	0.194	0.106	0.124
	(0.112)	(0.160)	(0.108)	(0.125)	(0.053)	(0.115)	(0.176)	(0.130)	(0.101)	(0.075)
Observations	555	555	555	555	555	555	552	553	555	555
R-squared	0.639	0.576	0.643	0.593	0.838	0.631	0.486	0.662	0.686	0.705
Sample	Ex. service occ.	Ex. serv. occ.+LS	Docum.	Undocum.	No Lat. Am.	Young	Young + <HS	Young + HS	Young + SC	Young +C

Note: This table shows regressions of the immigrant concentration on the city price index. Panel A presents OLS regressions, while panel B instruments the local price index by the housing supply elasticity estimated in Saiz (2010). Data come from the Census and ACS and include 185 MSAs and 68 sending countries for the years 1990, 2000, and 2010. Column 1 excludes workers in low-skill service occupation defined in Autor and Dorn (2013). Column 2 is the same regression as in column 1 but restricting the sample to low-educated workers. Column 3 includes only documented immigrants. Column 4 includes only undocumented immigrants, who are identified following Borjas (2017). Column 5 excludes immigrants from Latin American countries. Column 6 restricts the sample to young workers, aged below 45. Columns 7 to 10 restrict the sample to younger workers of each of the four education groups. Standard errors are clustered at the MSA level.

Table A.4—: Relative labor supply and the wage gap

	Dep. Var.: (ln) Wage Gap					
	(1) OP	(2) BGH	(3) Card	(4) Eq. (A.1)	(5) Eq. (A.1)	(6) Eq. (A.1)
Rel. labor supply	-0.036	-0.020	-0.031	-0.053	-0.014	-0.006
	(0.015)	(0.015)	(0.006)	(0.004)	(0.006)	(0.007)
Skill FE	Yes	Yes	No	Yes	Yes	Yes
MSE FE	No	No	No	No	Yes	No
MSA-year FE	No	No	No	No	No	Yes
Observations	120	120	124	5571	5571	5569
R-squared	0.791	0.763	0.809	0.287	0.390	0.138
1st stage F-stat			693.5	1108	398.3	285.0

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

Table A.5—: Immigrant-native wage gap and price levels

	Dep. Var.: (ln) Wage Gap							
	(1) OLS	(2) IV	(3) IV	(4) IV	(5) OLS	(6) IV	(7) IV	(8) IV
(ln) Price	-0.485	-0.479	-0.455	-0.509	-0.297	-0.317	-0.341	-0.232
	(0.073)	(0.085)	(0.113)	(0.079)	(0.080)	(0.126)	(0.125)	(0.110)
(ln) Population					-0.021	-0.020	-0.019	-0.025
					(0.005)	(0.008)	(0.007)	(0.007)
Observations	555	555	555	555	555	555	555	555
R-squared	0.406	0.406	0.405	0.405	0.464	0.463	0.462	0.460
IV	. .	WRLURI	Unavailable Land	Elasticity	.	WRLURI	Unavailable Land	Elasticity
1st stage F-stat		40.47	29.24	60.27		33.53	28.22	27.38

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

Table A.6—: Immigrant concentration and price levels, different network measures

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

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

Table A.7—: Immigrant concentration and price levels, different population measures

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

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

Table A.8—: Immigrant concentration and price levels, different groups of countries

	Dep. Var.: Immigrant concentration								
	Europe			South America			Other countries		
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML	(7) PPML	(8) PPML	(9) PPML
(ln) RER	0.652	0.088	-0.019	0.821	-0.268	0.122	-0.059	0.147	0.114
	(0.081)	(0.134)	(0.168)	(0.180)	(0.186)	(0.115)	(0.062)	(0.070)	(0.061)
(ln) Price	5.581	5.457	1.725	5.768	5.714	-1.455	3.749	3.870	1.590
	(0.462)	(0.448)	(0.470)	(0.462)	(0.438)	(0.814)	(0.281)	(0.264)	(0.429)
(ln) Price × (ln) RER	-1.641	-1.466	-1.517	-1.482	-1.502	-2.867	-2.700	-2.286	-1.674
	(0.589)	(0.534)	(0.436)	(0.840)	(0.757)	(0.684)	(0.596)	(0.585)	(0.436)
(ln) Population	0.084	0.084	0.142	0.236	0.236	0.525	0.163	0.160	-0.030
	(0.024)	(0.025)	(0.222)	(0.041)	(0.040)	(0.221)	(0.045)	(0.045)	(0.185)
Immigrant network	99.097	108.502	119.706	81.705	91.850	27.816	9.188	10.062	9.626
	(5.778)	(7.102)	(15.083)	(7.290)	(8.748)	(6.983)	(0.490)	(0.554)	(0.811)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
MSA FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	9990	9990	9990	4995	4995	4995	22755	22755	22755
R-squared	0.001	0.001	0.001	0.001	0.001	0.003	0.087	0.107	0.204

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

Table A.9—: Immigrants' homeownership rates

VARIABLES	(1) Ownership	(2) Ownership	(3) Ownership	(4) Ownership
Immigrant	-0.197	-0.125	-0.143	
	(0.0103)	(0.0104)	(0.0134)	
(ln) HH income		0.216	0.218	0.238
		(0.00516)	(0.00507)	(0.00830)
(ln) RER				0.00323
				(0.00850)
Observations	2,584,883	2,584,883	2,584,883	313,652
Year FE	yes	yes	yes	yes
MSA FE	yes	yes	no	yes
Sample	all	all	all	Imm. only

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

Table A.10—: Immigrant heterogeneity correlates

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

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

REFERENCES

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review*, 103(5): 1553–97.

Borjas, G. 2017. "The Labor Supply of Undocumented Immigrants." *Labour Economics.*

Borjas, G., J. Grogger, and G. Hanson. 2012. "On Estimating Elasticities of Substitution." *Journal of European Economic Association.*

Card, D. 2009. "Immigration and Inequality." *American Economic Review Papers and Proceedings*, 99(2): 1–21.

Hsieh, C.-T., and E. Moretti. 2019. "Housing Constraints and Spatial Misallocation." *American Economic Journal: Macroeconomics.*

Ottaviano, G., and G. Peri. 2012. "Rethinking the Effect of Immigration on Wages." *Journal of the European Economic Association*, 10(1): 152–197.

Ruist, J. 2013. "Immigrant-Native Wage Gaps in Time Series: Complementarities or Composition Effects?" *Economic Letters.*

Saiz, A. 2010. "The Geographic Determinants of Housing Supply." *Quartely Journal of Economics*, 125(3): 1253–1296.