Economics 250a
Local Labor Markets

Some key references

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Suphanit Piyapromdee (2013). "The Impact of Immigration on Wages, Internal Migration, and Welfare". University of Wisconsin Unpublished paper. Available at https://mywebspace.wisc.edu/piyapromdee/web/

David Card (2001) "Immigrant Inflows, Native Outflows, and the Local Market Impacts of Higher Immigration." JOLE 19(1).

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Overview

An area of increasing recent interest for labor economists is the study of local labor markets. From the labor perspective, it is important to understand how local labor supply shocks and labor demand shocks affect:

- local wages, employment, unemployment
- geographic mobility of workers (and firms)

There is also interest in how "local policies" (local taxes, special programs to encourage local growth) affect the local market. A key conceptual question is how the local market equilibrium is linked to the equilibrium in other local markets. Different papers take different stands on this. The benchmark case we will discuss to start this lecture assumes that workers are perfectly (and instantaneously) mobile across areas. This imposes a very strict "constant utility" constraint on workers in every location. Recent work takes away this assumption and tries to replace it with more reasonable assumptions about imperfectly elastic external supplies to each location.

A related conceptual question is how sector-specific sub-markets within each location are connected. Again, the benchmark case assumes that workers are perfectly (and instantaneously) mobile across sectors, so there is only a single wage for each *type* of labor in each location. This is the same assumption used in simple trade models. This assumption means that all workers of a given skill type in a given location are equally affected by sectoral shocks that hit the location.

Local shocks:

- on the supply side: immigration flows create location-specific shocks. Studies include Card (2001), Piyapromdee (2013). These shocks help identify the parameters of the local labor demand function. There is still substantial controversy over how the local demand function should be conceptualized.

- on the demand side: product demand shocks create differential shocks on net labor demand in different cities The classic "Bartik" demand shock variable is a weighted average of economy-wide employment shifts, where the weights reflect the relative fraction of local employment in each of the sectors. Most recently, Autor et al (2013) have examined the effects of trade-based product demand shocks. Local demand shocks help identify the parameters of the local labor supply function (broadly defined). As on the demand side, there is substantial controversy over how to model local supply.

Equilibrating forces:

There are 3 main equilibrating forces in local labor markets:

- external demand for locally produced goods/services. In the classic HO models of trade, external demand for each sector is infinitely elastic and local supply shocks can be absorbed by sectoral expansion (subject to a diversification constraint). Other models allow some elasticity in external demand (Altonji-Card, 1991) or completely ignore the issue

- mobility. Workers (and firms) can potentially move.

- land prices. Land prices reflect the net "value" of being in a given location. If a given location is highly productive for some external reason, land prices will capitalize this extra productivity.

Other factors:

The literature also looks at 2 other broad issues

- endogenous aggregation effects. Size and composition of the workforce may affect productivity of firms

- local policies - payroll taxes, sales taxes, land restrictions, development subsidies

Some key facts (from Moretti's Handbook chapter)

1. average wages vary a lot across cities (Tables 1 and 2), with somewhat larger variation in wages of college educated workers

	HS	College
San Jose	\$19.70	\$38.50
Abilene TX	\$11.90	\$19.70

2. real wages, adjusting for a simple index of local housing costs, are less variable across cities. Moreover, college grads are increasingly likely to live in high-cost cities, suggesting that some of the rise in average wages of college graduates is a (rising) compensating differential

3. different counties appear to have substantially different TFP (figure 5)

4. firms in similar manufacturing industries tend to be geographically clustered, suggesting the presence of local "natural advantages", or productivity spillovers, or some other form of agglomeration economy

The Roback Model

The basic "workhorse" model for thinking about local labor markets is presented by Roback. In the model there are homogenous workers and homogenous firms, who have to be indifferent between alternative cities. There is a single nationally traded good x that is produced by firms and consumed by workers, and sells at a constant price (normalized to 1). It is assumed that each worker has a non-labor income I that is independent of location: this can be rationalized by assuming every worker owns a share of the land in all cities.

A given city has an amenity value s: this can effect both workers' utilities and firms' costs. In a given city the wage is w and the rental rate on a unit of land is r. (For simplicity we ignore capital).[1] The number of workers who live in a city is N: each has utility function $u(x, l^c, s)$ where x is individual consumption, and l^c is the number of units of land consumed by a worker. A worker's indirect utility from living in a city with amenties s, wage w and land use price r is:

$$V(w, r, s) = \max_{x, l^c} u(x, l^c, s) \quad \text{s.t.} \quad x + rl^c - w - I = 0$$

Letting $\lambda = \lambda(w, r, s)$ represent the marginal utility of a dollar of income, notice that

$$\begin{aligned} V_w &= \lambda > 0 \\ V_r &= -\lambda l^c < 0 \end{aligned}$$

implying that

$$V_r = -l^c(w, r, s)V_w,$$

which is a variant of Roy's identify. On the firm side, each firm has CRS with *unit* cost function:

$$c(w, r, s)$$

Assuming total output of all firms in the city is X, total amount of land used by firms is L^p, and total employment is N, we have:

$$\begin{aligned} c_w &= N/X > 0 \\ c_r &= L^p/X > 0. \end{aligned}$$

[1] This can be justified as follows. Assume the production function is $X = g(N, L)^{1-\theta} K^\theta$, where X, N, L, K are output, labor, land, and capital, and $g(N, L)$ is homogeneous of degree 1. If capital is available at a rental rate q then setting the marginal product of capital equal to q leads to: $g(N, L)^{1-\theta} = (q/\theta)K^{1-\theta}$. Substituting into the production function we get $K = (\theta/q)X$. Then using this fact we can rewrite the production function as $X = g(N, L)\theta^{\theta/(1-\theta)} q^{-\theta/(1-\theta)}$,

Finally, there is a total land constraint:

$$L^p + Nl^c = L.$$

The indifference conditions for firms and workers across cities with different levels of s and endogenously varying wage and rents $w(s)$ and $r(s)$ respectively, are:

$$\begin{aligned} c(w(s), r(s), s) &= 1 && (1) \\ V(w(s), r(s), s) &= V^0. && (2) \end{aligned}$$

Differentiating w.r.t. s we have

$$\begin{bmatrix} c_w & c_r \\ V_w & V_r \end{bmatrix} \begin{bmatrix} w'(s) \\ r'(s) \end{bmatrix} = \begin{bmatrix} -c_s \\ -V_s \end{bmatrix}$$

and using the usual rules:

$$\begin{aligned} w'(s) &= \frac{V_r c_s - c_r V_s}{\Delta} \\ r'(s) &= \frac{V_s c_w - c_s V_w}{\Delta} \\ \Delta &= c_r V_w - c_w V_r. \end{aligned}$$

Note that we can re-write

$$\begin{aligned} \Delta &= c_r V_w - c_w V_r = \lambda L^p / X + \lambda l^c N / X \\ &= \lambda (L^p + l^c N)/X = \lambda L / X. \end{aligned}$$

As shown in Figures 1-3 there are several special cases of interest. Case 1 (Figure 1) is when $c_s = 0$ (ie., the amenity is only valued by consumers). Clearly in this case higher s is associated with higher rents and lower wages. The split between rents and wages is determined by the slope of relation between w and r implied by (1). Case 2 (Figure 2) is when $V_s = 0$ (i.e. the amenity has only a productivity effect). In this case a higher value of s leads to higher rents and higher wages, with the split detemined by the slope of the relation between w and r implied by (2). A third important benchmark (Figure 3) is when firms use no land and the amenity is non-productive. In this case equation (1) becomes $c(w(s)) = 1$, which means that the wage has to be the same in all locations. Setting $c_r = c_s = 0$:

$$\begin{aligned} w'(s) &= 0 \\ r'(s) &= \frac{V_s c_w}{-V_r c_w} = \frac{1}{l^c} \frac{V_s}{V_w}. \end{aligned}$$

This implies that the rise in the total cost of land for a given person who lives in a city with a higher value of s is:

$$l^c r'(s) = \frac{V_s}{V_w}.$$

The right hand side is the marginal willingness to pay for a change in s, so when $c_r = c_s = 0$, the marginal value of a change in the amenity is "fully capitalized" in rents.

How do we infer the value of amenities in the more general case? Let

$$\Omega(s) = V(w(s), r(s), s)$$

represent the total utility of living in city s, taking account of the endogenous adjustment of $w(s)$ and $r(s)$. If all cities have the same utility then

$$\Omega'(s) = V_w w'(s) + V_r r'(s) + V_s.$$

Re-organizing, and using the fact that $V_r = -l^c V_w$, we get:

$$\begin{aligned} V_s &= -V_w w'(s) + l^c V_w r'(s) \\ \rightarrow &\quad \frac{V_s}{V_w} = l^c r'(s) - w'(s). \end{aligned} \tag{3}$$

So the willingness to pay for the amenity can be obtained by looking at the combination of the extra land cost for consumers and the reduced wages in a higher-amenity city.

Some more insight can be obtained by looking at the firm side. Assuming that:

$$c(w(s), r(s), s) = 1$$

across different cities, then it must be true that

$$c_w w'(s) + c_r r'(s) + c_s = 0$$

Let's consider the case where $c_s = 0$. In this case,

$$\begin{aligned} w'(s) &= \frac{-c_r}{c_w} r'(s) \\ &= -\frac{L^p}{N} r'(s) \end{aligned}$$

So summing the willingness to pay of the N people in a given city we get

$$N \frac{V_s}{V_w} = N l^c r'(s) + L^p r'(s) = L r'(s).$$

In the case where firms use land but $c_s = 0$ we can get the aggregate value of the w.t.p. for the amenity by looking at how the total value of all land used in the city changes as we change s.

Finally let's consider the general case where $c_s \neq 0$. In this case the change in sum of consumer welfare and firm profits associated with a marginal change in s is the sum of aggregate consumer w.t.p and the cost-induced savings:

$$\begin{aligned} dSV &= N \frac{V_s}{V_w} - X c_s = N(l^c r'(s) - w'(s)) + X(c_w w'(s) + c_r r'(s)) \\ &= N l^c r'(s) + L^p r'(s) = L r'(s). \end{aligned}$$

So the total change in social value is just the change in the value of all land. Notice that this case encompasses all the previous special cases.

In her (very simple) empirical work, Roback estimated the effects of certain amentities (Z_c) on wages and residential rents. She estimated models of the form:

$$\begin{aligned}\log w_{ic} &= x_i\beta + \gamma_w Z_c + e_{ic} \\ \log r_c &= \gamma_r Z_c + \kappa_c\end{aligned}$$

The marginal value of a small change in amenity z is

$$\begin{aligned}\frac{V_s}{V_w} &= l^c r'(z) - w'(z) \\ &= w[\frac{l^c r}{w}\frac{r'(z)}{r} - \frac{w'(z)}{w}] \\ &= w[\theta\gamma_r - \gamma_w]\end{aligned}$$

where $\theta = \frac{l^c r}{w}$ is the share of residential land rent in income. Roback estimated this to be relatively small (3.5% on average): she estimated that mortgage costs represent ∼18% of income and land represents ∼20% of the value of a typical residential property. (These numbers are small by today's standards). She then sums the marginal values of a set of 10 or so amenities (including local crime rates, the unemployment rate, a measure of air pollution and measures of weather), and assigns valuations to different cities.

Roback also presents an extended model that has influenced subsequent analysts (e.g., David Albouy, "The Unequal Geographic Burden of Federal Taxation", JPE, August 2009). This model introduces a single non-traded local good "y" that is produced using land and local labor, and sells for a city-specific price p. Think of the local good as a composite of housing services and other non-housing services (restaurants, etc). Now the indirect utility function is

$$V(w,p,s) = \max_{x,y}\ u(x,y,s) \text{ s.t. } x + py = w + I$$

and there are 2 unit cost functions: one for the tradeable good (as before)

$$c(w,r,s) = 1$$

and another for the local good:

$$g(w,r,s) = p.$$

Now there are 3 endogenous variables (w,r,p), but the basic ideas in the preceding analysis are still present. An interesting application of this framework is to an amenity s that raises the cost of the local good, but has no inherent value for consumers or productivity effects on the traded sector. This could be inefficiency in the local construction sector, for example.

Allowing for Heterogeneity in Tastes

A major limitation of the Roback model is that all workers are indifferent to living in different cities. This is obviously false: a majority of people live in the state where they were born. Indeed, Severnini (2013) estimates that 80% of white couples live in a state where at least one of the two partners was born (though this ratio is only 33% if both have a PhD). Kline and Moretti (2013) present a very simple model based on Busso, Gregory and Kline (AER, 2013) in which people have idiosyncratic preferences for cities. They assume

$$u_{ic} = w_c - r_c + A_c - t + e_{ic}$$

where w_c and r_c are the levels of wages and rents in city c, A_c is an amenity in the city, t is a common (lump sum) tax, and e_{ic} is a taste factor. They assume e_{ic}/s is EV-1, which generates a MNL model. Notice that as $s \to 0$ people become more "attached" to specific cities, so s governs the elasticity of supply to a given city. The linearity of preferences is restrictive but greatly simplifies the analysis. They add a simple traded good sector that implies

$$\log w_c = d_0 + d \log \delta_c - \log(1 + \tau_c)$$

where δ_c is a TFP shifter, τ_c is a local wage tax or credit, d_0 is a constant that varies with the cost of capital, and d is another constant (KM use X_c as the symbol for δ_c). This means that the "labor demand curve" is horizontal in any city, but shifts up or down depending on δ_c. They complete the model with an inverse "housing supply" function:

$$r_c = z_c(N_c)^{k_c}.$$

Letting $v_c = w_c - r_c + A_c - t$, person i chooses city a over city b iff:

$$\frac{e_{ib} - e_{ia}}{s} \leq \frac{v_a - v_b}{s}$$

so

$$N_a = NF[\frac{v_a - v_b}{s}]$$

where N is the total population and F is the d.f. for a logit (the difference in 2 EV-1's). Setting $N = 1$ and re-arranging:

$$\begin{aligned} sF^{-1}(N_a) &= w_a - w_b - (r_a - r_b) + A_a - A_b \\ &= e^{d_0}(\frac{\delta_a^d}{1+\tau_a} - \frac{\delta_b^d}{1+\tau_a}) - (z_a(N_a)^{k_a} - z_b(1-N_a)^{k_b}) + A_a - A_b \end{aligned}$$

The lhs is an upward-sloping inverse-S shaped function of N_a, while the rhs is a negatively sloped function, leading to K-M's figure 1. They show how to use this simple model to discuss the effects of local tax/subsidy policies. An interesting extension is to the case where δ_c depends on the size of city c. If this effect is large enough, the rhs of the above equation can become upward sloping, leading to potential multiple equilibria (see KM figure 4).

Piyapromdee – Allowing for Different Skill Groups and Heterogeneity in Tastes

Piyapromdee is an ambitious attempt to extend the Roback type framework to allow different skill groups and taste heterogeneity. She assumes that workers are classified in 4 ways: education level (college/HS); gender; age (2 groups, young and old), and immigrant status. She assumes that each city has a 4-level nested CES production function producing a common traded good. The parameters of this model are estimated "stepwise", as in Card-Lemieux and Ottaviano-Peri, but using a combination of time and city-level variation (1980-1990-2000 Census plus 2007 ACS). The parameters for education, age and immigrant status are similar to those estimated by O-P. The estimated elasticity of substitution between men and women in the same education group is 1.9 (standard error=0.6), which is suprisingly small.

At the city level she assumes a housing supply model similar to the one in K-M. Specifically, she assumes a housing "rental rate" in city c in year t:

$$R_{ct} = i_t \times CC_{ct} \times [\sum_j \gamma_h H_{jct} + \sum_j L_{jct}]^{\gamma_c}$$

where i_t iis the interest rate in year t, CC_{ct} is an (unobserved) construction cost for city c in year t, H_{jct} is the number of high-education workers in subgroup j in city c in year t (so j runs over immigrants/natives + young/old + gender), L_{jct} is the number of low-ed. workers in group j, γ_h is a scale factor (=1.68 – see footnote 36), and γ_c is a city-specific supply elasticity that is allowed to vary with a measure of the fraction of undevelopeable land within 50 km of the center of each MSA area (so this is 1/2 for a city like Miami with a center very close to the ocean), and with an index of local land regulations (see equation 11, p. 13).

The final part of the model is a MNL choice model of preferences for different cities. The basic specification of utility is

$$U_{ict} = \max_{Q,G} \lambda_z \log(Q) + (1-\lambda_z)\log(G) + u_i(N_{ct}) + \sigma_z \epsilon_{ict} \text{ s.t. } P_t G + R_{ct} Q = W^z_{ct}$$

where: Q is an amount of housing (with local price R_{ct}), G is an amount of the numeraire good (with national price P_t), W^z_{ct} is the wage earned by a person in group $z = z(i)$ (based on education, gender, age, and immigrant status), λ_z is a housing share parameter that varies by education level only, ϵ_{ict} is an EV-1 error with scale σ_z, and $u_i(N_{ct})$ is a person-specific utility assigned to the "network characteristics" N_{ct} of city c in year t – this includes the fractions of various immigrant groups in the city in an earlier decade, which are valued differently by immmigrants from different source countries, as well as dummies for which state a city is in, which are valued differently by people who were born in different states. Doing the maximization we get:

$$\begin{aligned} U_{ict} &= \log(W^z_{ct}/P_t) - \lambda_z \log(R_{ct}/P_t) + u_i(N_{ct}) + \sigma_z \epsilon_{ict} \\ &= w^z_{ct} - \lambda_z r_{ct} + \beta_z X_{ict} + \sigma_z \epsilon_{ict} \end{aligned}$$

where P. is assuming that we can write $u_i(N_{ct}) = \beta_z X_{ict}$ (this is my notation for what she does). Note the functional form: indirect utility depends on log real wage (w_{ct}^z), and on the log of real housing prices (r_{ct}), but the weight on the real housing price depends on λ_i. If (for example) a person spends about 40% of their income on housing then we expect $\lambda_i = 0.40$. Re-normalizing the indirect utility by dividing by σ_z yields

$$\begin{aligned} U_{ict} &= \lambda_z^w (w_{ct}^z - \lambda_z r_{ct}) + \lambda_z^x X_{ict} + \epsilon_{ict} \\ &= \Gamma_{ct}^z + \lambda_z^x X_{ict} + \epsilon_{ict} \end{aligned}$$

where Γ_{ct}^z is the common value for city c in year t for all people in group z. Notice that all the "endogeneity" problems caused by endogenous variation in w_{ct}^z or r_{ct} are rolled into Γ_{ct}^z, while the person-specific component reflects interactions between a person's state of birth and the location of the city, or a person's country of birth and the shares of previous immigrants from the same country in the city 10 years ago. This leads to a two-step "micro-BLP" approach of estimating a MNL for location choice for person i that includes Γ_{ct}^z dummies and the person-specific components, then in the second stage the parameters for the determinants of Γ_{ct}^z are estimated using the estimates, $\widehat{\Gamma}_{ct}^z$.

P. estimates a model for the $\widehat{\Gamma}_{ct}^z$ terms in first-differences:

$$\Delta\widehat{\Gamma}_{ct}^z \equiv \widehat{\Gamma}_{ct}^z - \widehat{\Gamma}_{ct-10}^z = \lambda_z^w (\Delta w_{ct}^z - \lambda_z \Delta r_{ct}) + \Delta amenity_{ct}^z + sampling\ error$$

where $\Delta amenity_{ct}^z$ reflects the change in the (common) amenity value of city c to people in group z. Since changes in amenities may be correlated with wage/rent changes, instruments are needed. P uses "Bartik" shift-share instruments (based on lagged industry shares in the city and national changes in employment in each industry), interacted with the 2 shifters of local housing elasticity (the share of undevelopeable land, and the index of land use reguations). Note that P. calls the Bartik shock variables "Katz Murphy" indexes (KM). ((recall that P. treats $\lambda_z' s$ as known). Estimates of the key parameter $\lambda_z^w = 1/\sigma_z$ are reported in Table 5:

High-education natives	4.0
Low-education natives	3.7
High-education imms	1.2
Low-education imms	0.7

Table 1 Metropolitan areas with the highest and lowest hourly wage of high school graduates in 2000.

Metropolitan area	Average hourly wage
Metropolitan areas with the highest wage	
Stamford, CT	20.21
San Jose, CA	19.70
Danbury, CT	19.13
San Francisco-Oakland-Vallejo, CA	18.97
New York-Northeastern NJ	18.86
Monmouth-Ocean, NJ	18.30
Santa Cruz, CA	18.24
Santa Rosa-Petaluma, CA	18.23
Ventura-Oxnard-Simi Valley, CA	17.72
Seattle-Everett, WA	17.71
Metropolitan areas with the lowest wage	
Ocala, FL	12.12
Dothan, AL	12.11
Amarillo, TX	12.10
Danville, VA	12.08
Jacksonville, NC	12.02
Kileen-Temple, TX	11.98
El Paso, TX	11.96
Abilene, TX	11.87
Brownsville-Harlingen-San Benito, TX	11.23
McAllen-Edinburg-Pharr-Mission, TX	10.65

The sample includes all full-time US born workers between the age of 25 and 60 with a high school degree who worked at least 48 weeks in the previous year. Data are from the 2000 Census of Population.

The bottom panel in Fig. 2 shows the distribution of average hourly nominal wage for college graduates across metropolitan areas. (Note that the scale in the two panels is different.) The distribution of the average wage of college graduates across metropolitan areas is even wider than the distribution of the average wage of high school graduates. The 10th and 90th percentile of the distribution for college graduates are \$20.5 and \$28.5. This amounts to a 41% difference in labor costs. The 1st and 99th percentile are \$18.1 and \$38.5, respectively, which amounts to a 112% difference.

Table 1 lists the 10 metropolitan areas with the highest average wage for high school graduates and the 10 metropolitan areas with the lowest average wage for high school graduates. High school graduates living in Stamford, CT or San Jose, CA earn an hourly wage that is two times as large as workers living in Brownsville, TX or McAllen, TX with the same level of schooling. This difference remains effectively unchanged after accounting for differences in workers' observable characteristics. Table 2 produces a similar list for college graduates. The difference between wages in cities at the top of the distributions and cities at the bottom of the distribution is more pronounced for

Table 2 Metropolitan areas with the highest and lowest hourly wage of college graduates in 2000.

Metropolitan area	Average hourly wage
Metropolitan areas with the highest wage	
Stamford, CT	52.46
Danbury, CT	40.81
Bridgeport, CT	38.82
San Jose, CA	38.49
New York-Northeastern NJ	36.03
Trenton, NJ	35.52
San Francisco-Oakland-Vallejo, CA	34.89
Monmouth-Ocean, NJ	33.70
Los Angeles-Long Beach, CA	33.37
Ventura-Oxnard-Simi Valley, CA	33.07
Metropolitan areas with the lowest wage	
Pueblo, CO	20.16
Goldsboro, NC	20.15
St. Joseph, MO	20.01
Wichita Falls, TX	19.74
Abilene, TX	19.70
Sumter, SC	19.57
Sharon, PA	19.52
Waterloo-Cedar Falls, IA	18.99
Altoona, PA	18.68
Jacksonville, NC	18.21

The sample includes all full-time US born workers between the age of 25 and 60 with a college degree who worked at least 48 weeks in the previous year. Data are from the 2000 Census of Population.

college graduates. The average hourly wage of college graduates in Stamford, CT is almost three times larger than the hourly wage of college graduates in Jacksonville, NC. This difference is robust to controlling for worker characteristics.

The wage differences documented in Fig. 2 are persistent over long periods of time. While in the decades after World War II regional differences in income were declining (Barro and Sala-i-Martin, 1991), convergence has slowed down significantly in more recent decades. This can be seen in Fig. 3, where I plot the average hourly wage in 1980 against the average wage in 2000 for high school graduates and college graduates, by metropolitan area. The size of the bubbles is proportional to the number of workers in the relevant metropolitan area and skill group 1980. The lines are the predicted wages in 2000 from a weighted OLS regression, where the weights are the number of workers in the relevant metropolitan area and skill group in 1980.

The figure suggests that there has been no mean reversion in wages since 1980. In fact, the opposite has happened. Wage differences across metropolitan areas have *increased* over time. The slope of the regression line is 1.82 (0.89) for high school graduates. This

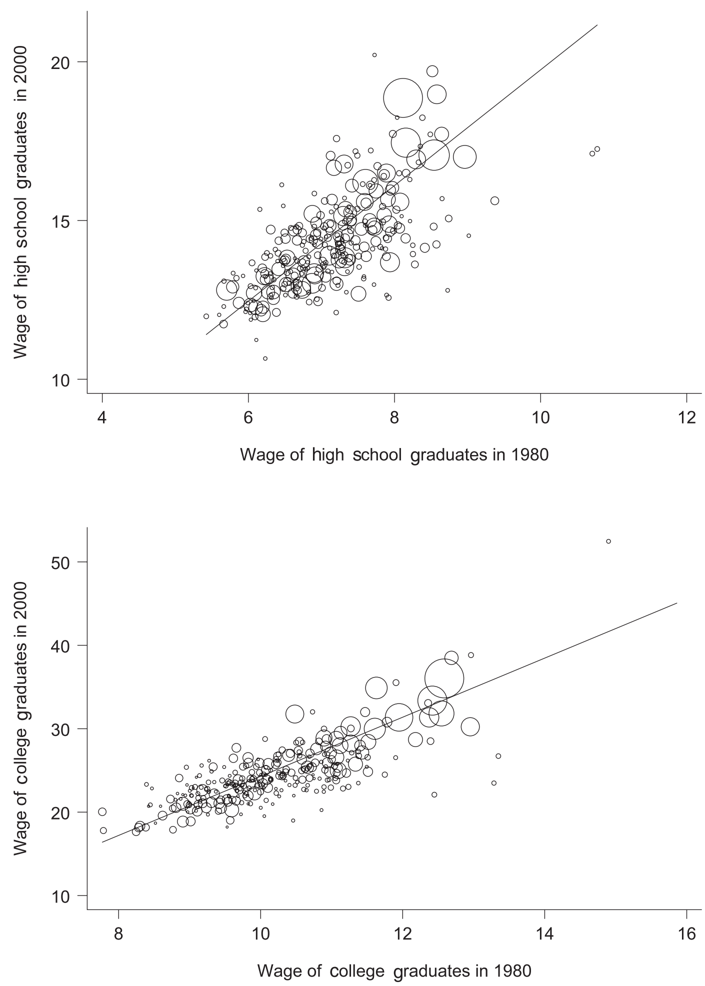


Figure 3 ***Change over time in the average hourly nominal wage of high school graduates and college graduates, by metropolitan area.*** Notes: Each panel plots the average nominal wage in 1980 against the average nominal wage in 2000, by metropolitan area. The top panel is for high school graduates. The bottom panel is for college graduates. The size of the bubbles is proportional to the number of workers in the relevant metropolitan area and skill group 1980. There are 288 metropolitan areas. The line is the predicted wage in 2000 from a weighted OLS regression, where the weights are the number of workers in the relevant metropolitan area and skill group in 1980. The slope is 1.82 (0.89) for high school graduates and 3.54 (0.11) for college graduates. Data are from the Census of Population. The sample includes all full-time US born workers between the age of 25 and 60 who worked at least 48 weeks in the previous year.

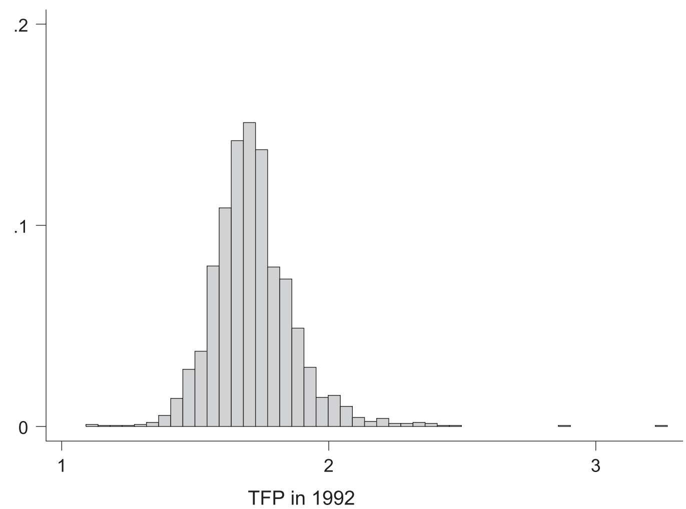


Figure 5 ***Distribution of total factor productivity in manufacturing establishments, by county.*** Notes: This figure reports the distribution of average total factor productivity of manufacturing establishments in 1992, by county. County-level TFP estimates are obtained from estimates of establishment level production functions based on data from the Census of Manufacturers. Specifically, they are obtained from a regression of log output on hours worked by blue and white collar workers, book value of building capital, book value of machinery capital, materials, industry and county fixed effects. The figure shows the distribution of the coefficients on the county dummies. Regressions are weighted by plant output. The sample is restricted to counties that had 10 or more plants in either 1977 or 1992 in the 2xxx or 3xxx SIC codes. There are 2126 counties that satisfy the sample restriction. For confidentiality reasons, any data from counties whose output was too concentrated in a small number of plants are not in the figure (although they are included in the regression).

coefficient equal to 0.513 (0.024).[4] Given that the share of income spent on housing is about 41% in 2000, this regression lends credibility to the notion that nominal wages adjust to take into account differences in the cost of living across localities.

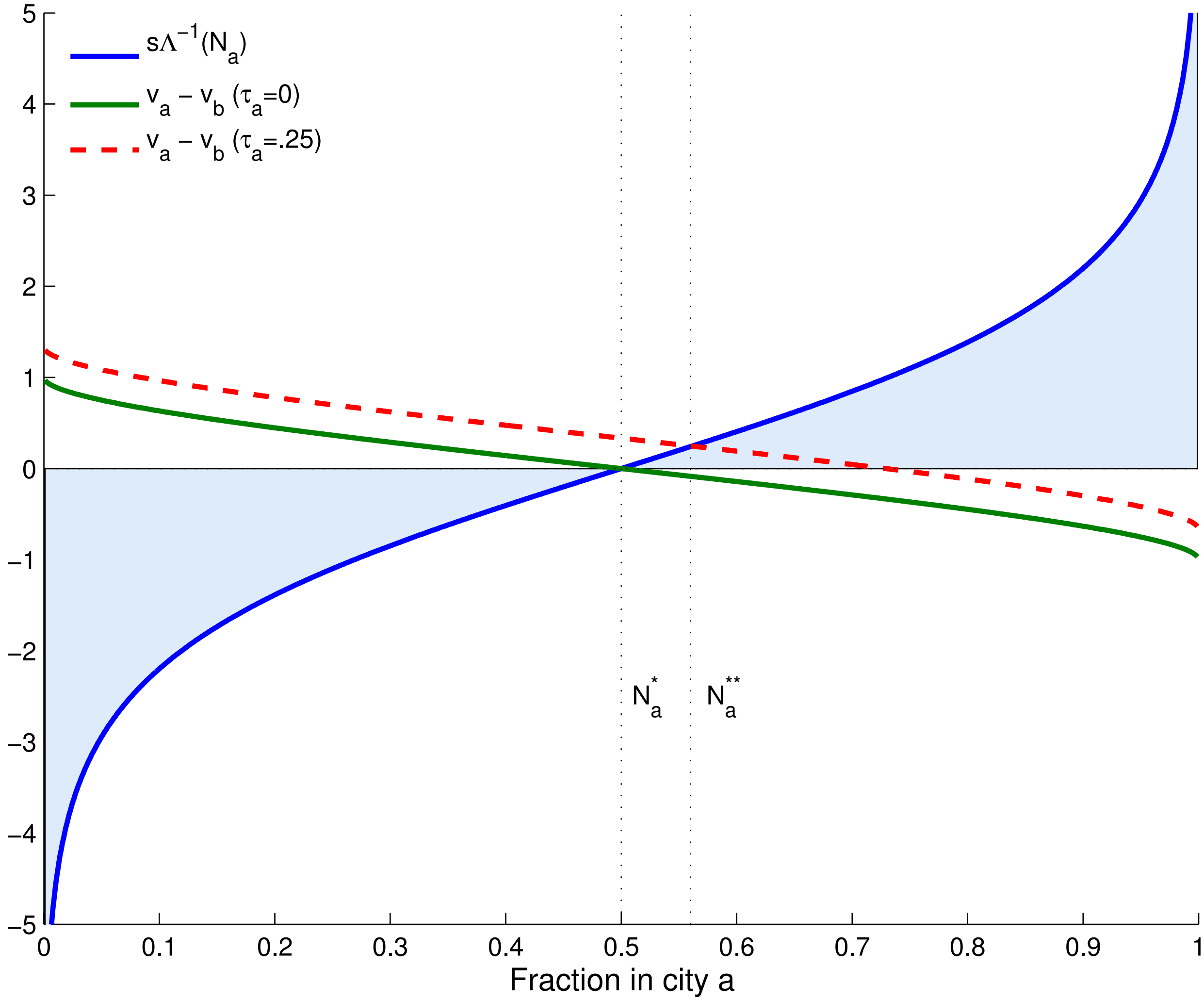
2.3. Productivity

The vast differences in nominal wages across local labor markets reflect, at least in part, differences in productivity. Productivity is notoriously difficult to measure directly. One empirical measure of productivity at the establishment level is total factor productivity (TFP), defined as output after controlling for inputs.

Figure 5 shows the distribution of average total factor productivity of manufacturing establishments in 1992 by county. County-level TFP estimates are obtained from estimates of production functions based on data from the Census of Manufacturers. Specifically, they are obtained from a regression of log output on hours worked by blue

[4] Data are from the 2000 Census of Population.

Figure 1: Equilibrium



as s approaches infinity, the blue line becomes nearly vertical as workers are willing to pay anything to locate in their preferred city.

Figure 1 can be used to assess graphically how the fraction of workers in city a changes in response to changes in location fundamentals. Increasing the supply of housing in city a (i.e. lowering z_a) reduces the slope of the green curve and increases N_a^*. An increase in either the amenity (A_a) or productivity (X_a) level of city a will shift the green curve up and increase the fraction of workers in that city while an increase in the amenity or productivity levels of city b will have the opposite effect.

A similar effect is generated by the introduction of a wage subsidy in city a. Because the wage subsidy makes it cheaper for firms to hire workers in a, the size of the city grows. Figure 1 shows that an increase of τ_a from zero to 0.25 raises the equilibrium fraction in city a from N_a^* to N_a^{**}. This new equilibrium yields a higher systematic component of utility in city a relative to city b, which means the economic rents accruing to prior residents of city a increase.

Table 5: Parameter Estimates

A. Worker preferences				
	High skill natives	Low skill natives	High skill immigrants	Low skill immigrants
Wage	4.028**	3.725**	1.228**	0.726**
	(0.122)	(0.059)	(0.014)	(0.019)
Implied Rent	-1.208	-1.341	-0.367	-0.247
B. Elasticity of Substitution				
σ_E: skill level	2.576**	σ_{M-H}: high-skill	12.903**	
	(0.577)	nativity	(2.480)	
σ_G: gender	1.924**	σ_{M-L}: low-skill	19.928**	
	(0.591)	nativity	(4.165)	
σ_A: age	8.315**			
	(2.701)			
C. Housing Supply Elasticities		D. Predicted Inverse Housing Supply Elasticities		
Land regulation	3.368**	Mean	0.211	
	(0.079)	SD	0.036	
Geo. constraints	1.223	Minimum	0.153	
	(1.152)	Maximum	0.336	
Base housing supply elasticity	1.605** (0.575)			

Standard errors in parentheses, clustered by MSA. **p<0.05, *p<0.1. Wage parameter estimates represent worker's demand elasticity with respect to local real wage in a small city. Implied rent preferences are the housing expenditure shares multiplied by worker's demand elasticity with respect to local real wage.

Table 6: Network Effects for Natives

	Young male high skill natives			Young female high skill natives		
	1990	2000	2007	1990	2000	2007
Birth state	2.947**	2.864**	3.086**	3.063**	3.186**	2.751**
	(5.0E-6)	(5.8E-6)	(8.4E-6)	(5.7E-6)	(8.2E-6)	(3.0E-6)
Distance (1000 miles)	-0.631**	-0.648**	-0.582**	-0.632**	-0.567**	-0.896**
	(3.8E-6)	(4.2E-6)	(4.4E-6)	(4.3E-6)	(4.5E-6)	(4.8E-6)
	Old male high skill natives			**Old female high skill natives**		
	1990	2000	2007	1990	2000	2007
Birth state	2.598**	2.512**	2.82**	2.437**	2.707**	2.369**
	(1.1E-5)	(7.0E-6)	(7.8E-6)	(1.3E-5)	(9.9E-6)	(3.9E-6)
Distance (1000 miles)	-0.767**	-0.781**	-0.617**	-0.925**	-0.742**	-0.978**
	(9.5E-6)	(6.2E-6)	(5.3E-6)	(1.3E-5)	(7.7E-6)	(6.3E-6)
	Young male low skill natives			**Young female low skill natives**		
	1990	2000	2007	1990	2000	2007
Birth state	3.808**	3.82**	3.92**	3.482**	3.754**	3.847**
	(7.6E-6)	(9.8E-6)	(1.1E-5)	(6.5E-6)	(1.2E-5)	(1.4E-5)
Distance (1000 miles)	-0.556**	-0.524**	-0.506**	-0.771**	-0.599**	-0.569**
	(7.0E-6)	(6.5E-6)	(7.0E-6)	(8.8E-6)	(8.1E-6)	(9.6E-6)
	Old male low skill natives			**Old female low skill natives**		
	1990	2000	2007	1990	2000	2007
Birth state	2.885**	3.683**	3.445**	3.14**	3.376**	3.372**
	(6.7E-6)	(1.2E-5)	(7.0E-6)	(1.2E-5)	(1.0E-5)	(7.0E-6)
Distance (1000 miles)	-1.163**	-0.53**	-0.672**	-1.013**	-0.738**	-0.739**
	(1.4E-5)	(9.2E-6)	(8.4E-6)	(1.4E-5)	(9.3E-6)	(9.2E-6)

Standard errors in parentheses. **p<0.05, *p<0.1.

Table 7: Network Effects for Immigrants

	Young male high skill immigrants			Young female high skill immigrants		
	1990	2000	2007	1990	2000	2007
Number of previous immigrants from same country (in million)	2.273**	1.402**	0.991**	2.432**	1.644**	1.146**
	(1.0E-4)	(4.8E-5)	(2.9E-5)	(1.3E-4)	(5.6E-5)	(3.4E-5)
	Old male high skill immigrants			**Old female high skill immigrants**		
	1990	2000	2007	1990	2000	2007
Number of previous immigrants from same country (in million)	2.485**	1.683**	1.205**	2.673**	2.046**	1.391**
	(2.6E-4)	(1.0E-4)	(4.8E-5)	(3.3E-4)	(1.3E-4)	(5.9E-5)
	Young male low skill immigrants			**Young female low skill immigrants**		
	1990	2000	2007	1990	2000	2007
Number of previous immigrants from same country (in million)	2.445**	1.601**	1.245**	2.602**	1.762**	1.38**
	(2.9E-5)	(1.4E-5)	(9.4E-6)	(5.1E-5)	(2.4E-5)	(1.8E-5)
	Old male low skill immigrants			**Old female low skill immigrants**		
	1990	2000	2007	1990	2000	2007
Number of previous immigrants from same country (in million)	3.061**	1.809**	1.328**	3.015**	1.885**	1.419**
	(9.0E-5)	(2.6E-5)	(1.3E-5)	(1.1E-4)	(3.3E-5)	(1.8E-5)

Standard errors in parentheses.**p<0.05, *p<0.1.