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The Supply and Demand of Skilled Workers in Cities and the Role of Industry Composition

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Abstract

The share of high-skilled workers in U.S. cities is positively correlated with city size, and this correlation strengthened between 1980 and 2010. Furthermore, during the same time period, the U.S. economy experienced a significant structural transformation with regard to industrial composition, most notably in the decline of manufacturing and the rise of high-skilled service industries. To decompose and investigate these trends, this paper develops and estimates a spatial equilibrium model with heterogeneous firms and workers that allows for both industry-specific and skill-specific technology changes across cities. The estimates imply that both supply and demand of high-skilled labor have increased over time in big cities. In addition, demand for skilled labor in large cities has increased somewhat within all industries. However, this aggregate increase in skill demand in cities is highly concentrated in a few industries. The finance, insurance, and real estate sectors alone account for 35 percent of the net change over time.

JEL Classifications: R12, J21, J61

Keywords: Production, Amenities, Cities, Skilled Labor

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1 Introduction

A well-documented fact in geography and economics is that economic activity is highly concentrated spatially in regions and cities. Additionally, locations with large concentrations of employment and firms exhibit higher prices and wages. This suggests that some production or trade efficiencies result from proximity, although consumption amenities may play a role as well. Nonetheless, all types of workers and firms do not exhibit the same levels of spatial concentration. Take, for example, the New York City labor market, which accounts for 6.3 percent of total employment in the United States. Looking at industries separately, New York accounts for 8.8 percent of employment in the finance, insurance, and real estate industries but only 3.7 percent of manufacturing employment. Likewise, when looking at educational attainment among workers, we find that New York accounts for 8.0 percent of all workers with college degrees in the United States. This example suggests that heterogeneity among workers and firms can lead to some sorting across locations.

It is also likely that the distribution of industries and the distribution of skilled workers are related. Recent trends in the location and composition of both industries and skilled labor reinforce the importance of understanding this relationship. Skilled workers have long been overrepresented in large cities. However, the correlation between the skill level of the workforce and city size grew significantly between 1980 and 2010. In addition, industry composition changed drastically, in particular regarding the decline of manufacturing, which accounted for 20 percent of employment in 1980 and only 12 percent in 2010. These losses were largely made up through employment gains in service sectors, including health care, education, business services, and professional services.

The objective of this paper is to decompose and analyze the interrelated sorting of skilled workers and industries into large cities while taking into account that consumption amenities across cities may vary in an analogous way to productivity, thus constructing a more complete account of supply and demand of skilled workers across cities. Previous literature has mostly addressed these various topics separately and finds significant effects for all of them.

The concentration of industries is often attributed to agglomeration externalities, and research has shown that these agglomeration effects differ across industries.[1] For example, Henderson, Kunkoro, and Turner (1995) and Deckle and Eaton (1999), among others, found differences in agglomeration effects in relatively high-skilled versus low-skilled industries.

Other literature has focused on the relationship between cities and skilled workers. In particular, Moretti (2004) and others have shown that higher shares of skilled workers in cities lead to positive production externalities for all workers in a city, with higher benefits for skilled workers.[2] Furthermore, Baum-Snow and Pavan (2012) show that city size is correlated with wage inequality and that changes in inequality in larger cities account for a substantial proportion of the changes in overall wage inequality. Additionally, Baum-Snow, Freedman, and Pavan (2014) attribute most of these changes in inequality to skill bias of agglomeration economies. Finally, Davis and Dingel (2014) propose a theory of city structure and agglomeration to explain the sorting of high skilled workers into cities.

Several researchers have noted that the role of cities has changed over time, moving from sectoral or industry centers to concentrations of tasks or skills. This includes work by Davis and Henderson (2008), Duranton and Puga (2005), and Michaels and Redding (2013). This is also related to the international literature on task trade, including work by Grossman and Rossi-Hansberg (2008), who suggest that trade in intermediate tasks, as opposed to final goods, is becoming more prominent due to improvements in transportation and communication technology.

Additionally, research has shown that consumption amenities play an important role in the value of cities, although the absolute relationship between city size and amenity value is unclear. Separate estimates of the consumption value of amenities in cities are provided by Chen and Rosenthal (2008) and Albouy (2008). Rappaport (2008) shows that amenities are strongly correlated with density and, using a calibrated structural model, shows that

[1]For a review of the empirical literature on agglomeration see Rosenthal and Strange (2004). For theoretical foundations, see Fujita and Thisse (2002) and Duranton and Puga (2004).

[2]Work by Lin (2011), Bacolod, Blum, and Strange (2009), and Combes, Duranton, and Gobillon (2008) provides further empirical evidence on the nature of these externailities for skilled workers and the sorting of skilled workers across locations.

consumption amenities can account for a significant proportion of the variance in density across space. Lee (2010) and Handbury (2014) both argue that consumption amenities vary across worker types due to increasing tastes for variety with either income or skill level. Finally, Albouy (2009) estimates the separate effects of production and consumption amenities in wage and price differences across cities, finding a larger role for production. Diamond (2013) takes this a step further, allowing for heterogeneity across workers in both preferences and productivity across locations.

This paper deviates from previous literature by explicitly examining the relationship among skills, industries, and cities. The first goal of this paper is to use data on individual workers to document some of the basic correlations found in the joint distributions of education levels, industries, and cities. Some notable patterns arise from this analysis. First, high-skilled workers are overrepresented in large cities and are paid relatively higher wages than less-skilled workers. In addition, these correlations have strengthened over time. Furthermore, industry-specific employment is systematically correlated with both city size and education levels. Finally, industries associated with higher skill levels have gained employment share, while low-skilled industries have declined.

Next, we develop a spatial equilibrium model to help disentangle the complex relationships found in the data and to help illuminate the underlying mechanisms of location choices and labor markets. The model is built by starting with the work of Rosen (1979) and Roback (1982), who provided the insight that the wages and rents observed across cities can be used to measure the relative production and consumption value of a location. We then add a discrete choice framework to fully characterize the supply and demand of heterogeneous workers across locations. Preferences for city amenities are allowed to vary across worker types. In addition, industry-specific production functions vary across locations. Differences in the productivity of a location for each industry can arise through industry-specific total factor productivity (TFP) changes, as is standard in modeling agglomeration externalities, but differences can also come from skill-specific technological changes in labor productivity. This allows us to consider the separate roles of skill-specific versus industry-specific advantages of cities.

Finally, the model is used to estimate structural parameters that capture the production function and preferences for heterogeneous industries and skill types. The model is estimated using a maximum likelihood estimator derived from the discrete choice structure. The estimated parameters are then used to define the supply and demand of skilled workers across cities. In addition, the estimates are used to decompose the role of separate industries on the sorting of skilled workers. For the most part, the results focus on how supply and demand for skilled workers change with city size.

We find that the amenities offered by large cities are valued more by high-skilled workers than by low-skilled workers. Furthermore, this gap has widened over time. In 1980, for a 1 percent change in total city employment, the supply of high school graduates increased only 0.94 percent, holding prices constant, compared with 1.02 percent for college graduates, for a difference of 0.07 percent. In 2010, this gap rose to 0.12 percent (0.95 for high school graduates and 1.07 for college graduates).

While the supply of skilled labor is important, demand for skilled workers through increased productivity is a bigger driver of the sorting of educated workers into large cities. Like supply, the gap in demand for skilled workers in cities has increased over time. In 1980, the demand for high school workers increased 0.95 percent for every 1 percent gain in total city employment, holding prices constant, compared with a 1.07 percent gain in college graduates, for a difference of 0.13 percent. These elasticities changed to 0.88 percent for high school graduates and 1.11 percent for college graduates, for a difference of 0.23 percent in 2010.

To get a better sense of what drives the change in skill demand across cities, we decompose the demand into two components. We refer to the first as an industry-specific component of skilled labor demand, which arises from different changes in industry TFP in larger cities (i.e., industry-specific agglomeration effects), which may be correlated with the average skill level of industries. This component alone leads only to a 0.03 percent difference in relative demand elasticities for high school and college graduates for a 1 percent increase in city employment. The second component, which we refer to as the skill-specific component, arises from changes in skill demand within industries across cities. Shifts in skill demand are dominant and account for a 0.20 percent difference in relative demand elasticities for high school and college graduates, for a 1 percent increase in total city employment. Additionally, this gap has increased significantly over time. This result confirms the hypothesis that cities are becoming increasingly concentrated in specific tasks rather than industries. In fact, within every industry, relative demand for high-skilled labor is somewhat higher in large cities.

However, a few industries account for a disproportionate share of skilled-labor demand in large cities. There is significant variation across industries in the response of TFP to city size. In addition, certain industries exhibit much more flexibility in adjusting the skill composition of their workforce across cities. For example, TFP in the education industry increases very little with city size, and the eduction industry exhibits a fairly uniform skill composition in all cities. The finance industry, on the other hand, exhibits large changes in productivity with increased city size and significantly increases its expenditure shares on high-skilled labor in large cities. Additionally, these composition effects in the finance industry have increased over time. In fact, increases in the demand for high-skilled labor from the finance industry alone account for 35 percent of the total net change in skilled labor demand in large cities between 1980 and 2010.

The rest of the paper is organized as follows. Section 2 introduces the data and establishes some empirical regularities regarding the joint distribution of skills, industries, and cities. Section 3 outlines a spatial equilibrium model of production and consumption with heterogeneous industries and worker types. Section 4 details the estimation strategy. Section 5 presents the quantitative results. Finally, Section 6 concludes.

2 Data and Descriptive Statistics

In this section, we present some of the basic empirical regularities that characterize the distribution of workers and industries across cities, paying special attention to the role of city size. We also focus on the differences in spatial distribution of workers by skill, proxied by education, as is common in the literature. We will look at data from 1980 to 2010, to note some of the important changes that have occurred over this time period with respect to industry and worker composition.

The data for this section, as well as for the estimation and quantitative analysis presented subsequently, are drawn from IPUMS-USA.[3] The data are representative microdata drawn from the U.S. decennial census and the American Community Survey and offer information on education, income, location, industry, house prices and rents, and housing characteristics. The geographic units we consider are U.S. metropolitan statistical areas (MSAs), which will be interchangeable with the term "city" for the remainder of this paper. We drop non-MSA locations from the data, and we also drop MSAs for which there is not complete data for all years. Overall, we study 219 MSAs for 1980, 1990, 2000, and 2010.[4]

One persistent fact in the data is that larger cities tend to contain a larger share of skilled workers. Figure 1 plots the share of college-educated workers versus the natural log of total employment across cities for 1980 and 2010. First note that educational attainment overall has increased, as evidenced by the upward shift. But more important, there is also a clear correlation between city size and skill levels, and this correlation has strengthened over the 30-year period.

The correlation between skills and city size suggests that cities hold some relative advantages for high-skilled workers, through either production or consumption. Figure 2 provides evidence that production plays some role in the overrepresentation of skilled workers in large cities. The figure plots the relationship between mean log wages and log total employment for workers with and without college degrees. Note that wages increase with city

[3]The data are availble due to work by researchers at the University of Minnesota (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010)) and are publicly available at https://usa.ipums.org/usa/index.shtml

[4]Some additional processing was necessary to use the data. First, we only use high-level industry categories in order to make the analysis intuitive. Some judgment was used to decide how to group industries. The military sector was removed altogether, given that it does not apply particularly well to this analysis. We also only considered workers who were employed and removed some income outliers. More information on how the final data set was constructed is available upon request.

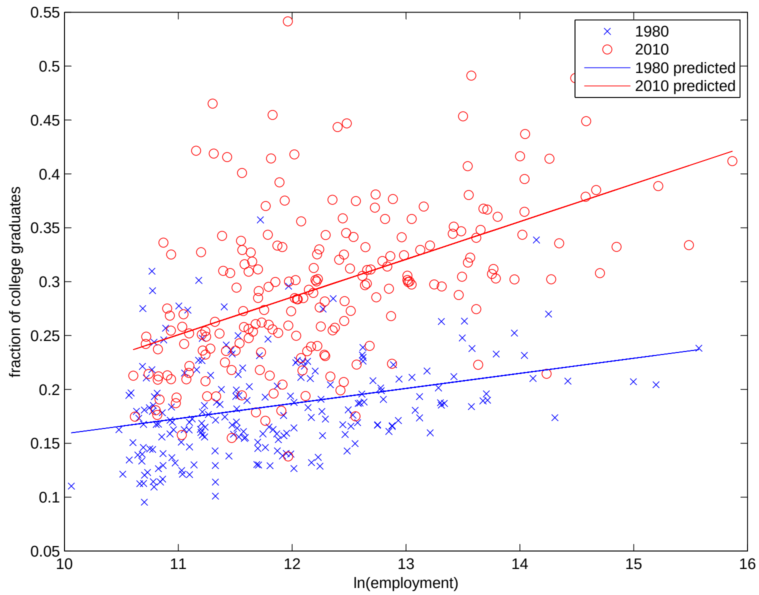

Figure 1: City size and education, 1980 and 2010. Source: IPUMS-USA data for 219 selected MSAs

size for both groups, but the slope is somewhat steeper for college-educated workers. The willingness of firms to incur higher labor costs suggests a productivity advantage, and that this productivity advantage benefits high-skilled workers more than others. However, the general equilibrium consequences of this productivity advantage are unclear without considering the role of amenities. In other words, the effect of increased demand on wages can be more or less pronounced depending on how workers value the amenities of large cities.

Additionally, the sorting of skilled labor and wage differences across cities may not be completely due to skill-biased productivity increases in cities but instead might arise from industry productivity advantages in cities for industries that employ varying shares of different labor types. In other words, the observed empirical patterns could be a result of industry-specific agglomeration externalities that act on total factor productivity rather than skill-specific effects.

Table 1 presents the unsurprising fact that different industries employ very different mixes of skill levels. Consider the example of durable goods manufacturing versus finance,

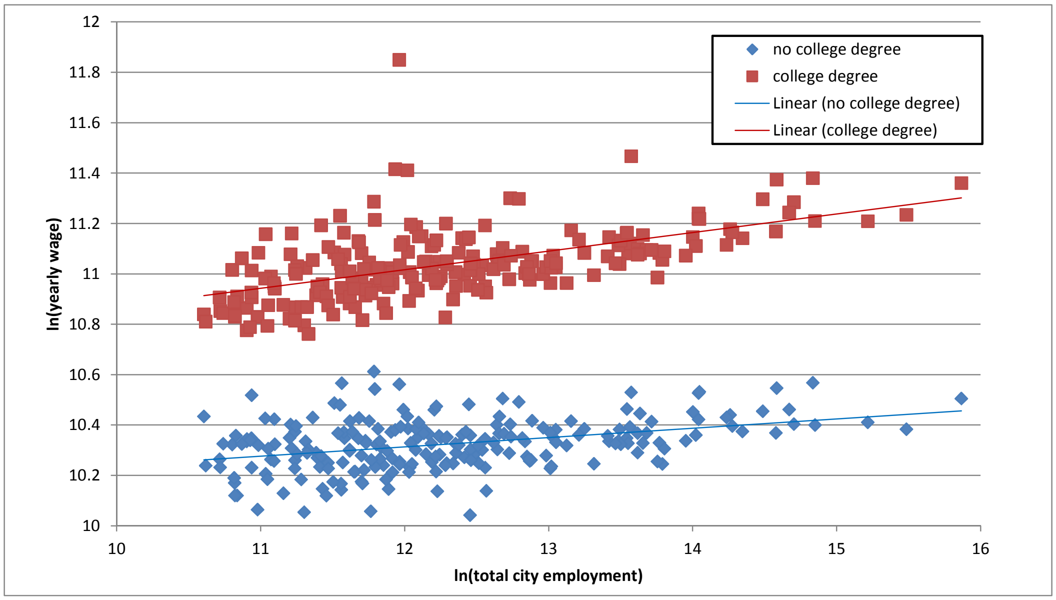

Figure 2: City size and wages by education level, 2010. Source: IPUMS-USA data for 219 selected MSAs

insurance, and real estate. The finance industry employs significantly more college graduates and significantly fewer workers with a high school education. In isolation, this reveals nothing about the distribution of skill types or wages across cities. However, if certain industries are more heavily concentrated in cities than others, this could contribute to the sorting of skilled workers. Figure 3 shows the correlation with industry employment share and city size for the two industries mentioned above. Notice that finance, an industry that employs a relatively high share of skilled workers, is heavily concentrated in cities, whereas durable goods manufacturing is the converse.

Finally, if we want to understand the changes in the sorting and wages of workers with different skills over time, we cannot ignore that the composition of industries in the U.S. and other advanced economies has changed drastically over recent decades. Table 2 shows the change in industry employment share between 1980 and 2010. The most obvious change is the decline in both durable and nondurable manufacturing and the increase in service sectors, most of which are high skilled. Depending on the productivity advantages

Table 1: Percentage of Workers in Education Group by Industry in 2010

	< High School	High School	Some College	College	Graduate School
Retail Trade	13.95	41.08	28.89	13.39	2.69
Education	2.40	15.53	17.21	28.66	36.19
Health Care	3.74	24.09	32.89	21.46	17.82
Durable Goods	9.05	36.89	22.93	20.96	10.17
Finance, Insurance and Real Estate	2.27	24.04	26.97	34.67	12.05
Business and Repair Services	10.11	31.99	24.01	24.91	8.98
Construction	19.98	45.05	21.65	10.80	2.53
Nondurable Goods	12.33	36.21	20.26	21.92	9.29
Public Administration	1.71	23.69	31.02	27.15	16.42
Transportation	7.72	44.34	29.31	15.35	3.29
Social Services	6.52	26.55	26.14	25.04	15.75
Professional Services	1.64	14.11	19.23	41.06	23.96
Personal Services	15.82	40.54	26.26	14.04	3.34
Wholesale Durable Goods	7.14	36.18	26.89	23.92	5.87
Agriculture, Forestry and Fisheries	33.38	32.89	17.09	11.10	5.55
Wholesale Nondurable Goods	11.26	35.46	23.72	23.58	5.99
Communications	1.77	24.00	31.42	32.02	10.79
Entertainment and Recreation	10.84	32.37	30.50	21.63	4.66
Legal Services	0.89	15.94	21.20	17.12	44.85
Utilities and Sanitary Services	6.64	37.98	27.41	19.79	8.18

Source: IPUMS-USA data for 219 selected MSAs

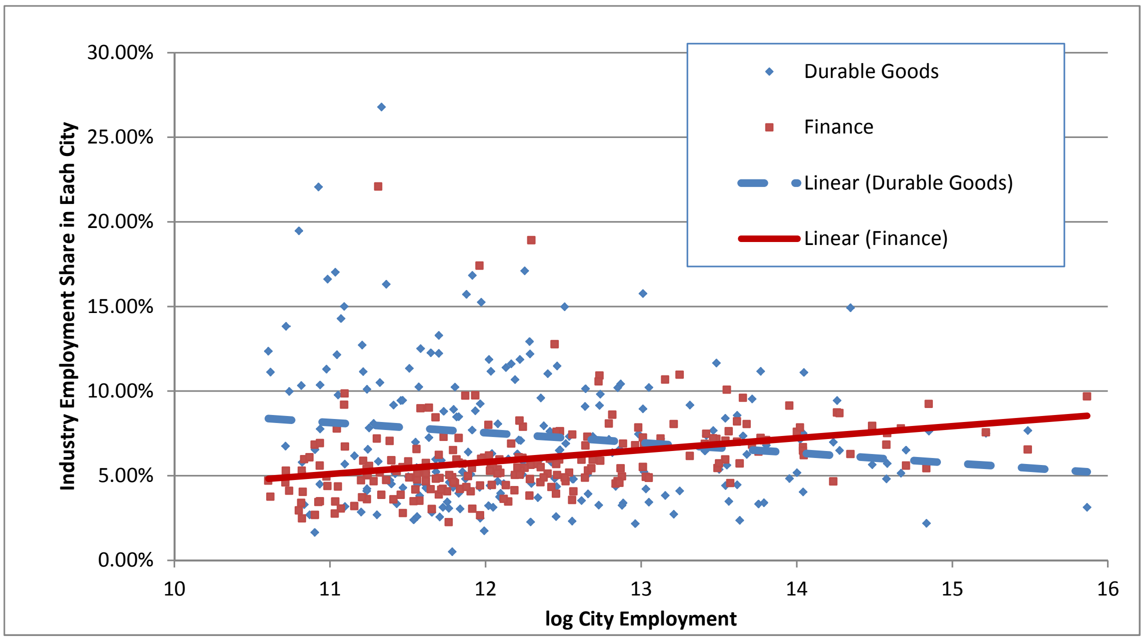

Figure 3: City size and employment share for select industries in 2010. Source: IPUMS-USA data for 219 selected MSAs

of cities for these different industries, this may or may not be contributing to the increased concentration of high-skilled workers in large cities.

Table 2: Percentage of Total Employment by Industry for 1980 to 2010

	% of total employment				
Industry	1980	1990	2000	2010	change 1980-2010
Retail Trade	15.86	16.55	16.71	18.24	2.38
Education	8.77	8.57	9.38	10.17	1.40
Health Care	7.74	8.70	9.05	10.95	3.21
Durable Goods	14.63	10.84	9.17	6.63	-8.00
Finance, Insurance and Real Estate	7.03	7.90	7.37	6.99	-0.03
Business and Repair Services	3.71	4.99	6.53	6.51	2.80
Construction	5.12	5.57	5.92	5.37	0.25
Nondurable Goods	8.09	6.47	5.24	3.92	-4.16
Public Administration	5.83	5.16	4.98	5.28	-0.55
Transportation	4.83	4.77	4.81	4.33	-0.49
Social Services	2.25	2.80	3.62	4.48	2.23
Professional Services	2.03	2.59	3.40	3.69	1.66
Personal Services	2.75	2.97	2.71	3.06	0.31
Wholesale Durable Goods	2.59	2.73	2.16	1.50	-1.09
Agriculture, Forestry and Fisheries	1.63	1.63	1.40	1.84	0.21
Wholesale Nondurable Goods	2.16	2.14	1.77	1.53	-0.63
Communications	1.73	1.65	1.81	1.43	-0.30
Entertainment and Recreation Services	1.11	1.51	1.61	1.70	0.59
Legal Services	0.75	1.19	1.22	1.20	0.45
Utilities and Sanitary Services	1.39	1.28	1.15	1.16	-0.23

Source: IPUMS-USA microdata for 219 selected MSAs

3 The Model

While the statistics described previously provide some insight into the economic fundamentals driving the sorting of skill levels across locations, more rigorous analysis is needed to untangle the relative magnitude of skill and industry components and to analyze general equilibrium effects. Therefore, this section develops a spatial equilibrium model of the labor market that considers the production technologies of heterogeneous industries over different skill types. The model also allows for both industry-specific and skill-specific productivity changes across space. Finally, the model allows for differences in preferences for city amenities across worker types, to better capture the supply of labor across cities.

The basic framework of the model builds on the research of Rosen (1979) and Roback (1982), who proposed the idea that the productivity and amenity value of locations can be inferred by observing local prices, given that people and firms are mobile. More specifically, higher input prices suggest that productivity is higher for firms. On the consumer side, higher local prices and lower wages suggest higher amenity value for a location. When land or housing markets are included, the framework can be used to model city population distributions as well.

However, more machinery is needed to understand the role of agent heterogeneity, both idiosyncratic and systematic, in equilibrium, particularly when it comes to understanding relative quantities of labor types across space. Therefore, the current model allows for firms that operate in distinct industries with technologies over different skilled labor inputs and different preferences across worker types. In addition, a discrete choice framework is embedded in the model to explain the idiosyncratic component of location decisions and to aid in empirical analysis. With this, the model delivers a more complete representation of the supply and demand of heterogeneous workers across cities.

We will now consider an economy with I worker types, J industries, and K locations.

3.1 Workers and Labor Supply

3.1.1 Preferences

The population of N workers is divided into $i \in \{1, I\}$ groups, corresponding to different worker types. Worker types are innate and the population of each type of worker is fixed at N_i. N_{ik} represents the population of each type in each location, such that

$$\sum_k N_{ik} = N_i.$$

In addition, each worker supplies one unit of labor inelastically at a single location and receives a local market wage, w_{ik}.

Workers have increasing preferences over consumption of J types of goods, denoted c_j; housing, l_k; and an aggregate location-specific amenity, $\widetilde{B}_{ik}$. Each worker maximizes utility subject to location specific wages, rents, and goods prices. Preferences differ across worker types in the relative valuation of location-specific amenities. In addition, individual workers have some idiosyncratic preference over locations, denoted by $\varepsilon_{k,m}$, distributed i.i.d. The subscript m denotes an individual worker.

Assuming a Cobb-Douglas form, preferences of a given worker type in a given location are defined by

$$U_{ik,m}(l,q) = \varepsilon_{ik,m}\widetilde{B}_{ik}l_k^{\theta}\left[\prod_j c_{ijk}^{\zeta_j}\right]^{1-\theta},$$

where $\widetilde{B}_{ik}$ is the location specific amenity and θ is the housing share of consumption.

3.1.2 Labor Supply across Locations

For simplicity, we will assume that goods prices are fixed, constant across locations, and exogenously given, allowing for the following notational simplifications:[5]

$$\prod_j c_{ijk}^{\zeta_j} = c_{ik} \text{ and } p_{jk} = p = 1.$$

The maximization problem for each worker type in each location can the be written as:

$$\max_{c_{ik}} U_{ik,m}(c_{ik};\widetilde{B}_{ik}) = \varepsilon_{k,m}\widetilde{B}_{ik}l_k^{\theta}c_{ik}^{1-\theta}$$

$$s.t.\ w_{ik} = r_k l + c_{ik}. \tag{1}$$

Indirect utility is then given by

[5]This is a reasonable assumption for goods with low shipping costs but is a stretch for goods with high shipping costs or nontradables such as local services.

$$V_{ik,m}(w_{ik}, r_k; \widetilde{B}_{ik}) = \theta^{\theta}(1-\theta)^{(1-\theta)}\varepsilon_{k,m}\widetilde{B}_{ik}\tfrac{w_{ik}}{\theta r_k}.$$

Workers are perfectly mobile and will choose the location that provides the highest utility level. Using standard discrete choice theory, we can then write the probability that a worker of a given type chooses a given location conditional on amenities and wages, using the following:

$$P_i^S(k|\widetilde{B}_{ik}, w_{ik}, r_k) = \frac{\exp(\ln \widetilde{B}_{ik} + \ln w_{ik} - \theta \ln r_k)}{\sum\limits_k \exp(\ln \widetilde{B}_{ik} + \ln w_{ik} - \theta \ln r_k)}. \tag{2}$$

The total supply of a given worker type in a given location, N_{ik}^S, is then given by

$$N_{ik}^S\left(\widetilde{B}_{ik}, w_{ik}, r_k\right) = N_i \tfrac{\exp(\ln \widetilde{B}_{ik} + \ln w_{ik} - \theta \ln r_k)}{\sum\limits_k \exp(\ln \widetilde{B}_{ik} + \ln w_{ik} - \theta \ln r_k)}.$$

Also, assume that $\widetilde{B}_{ik}$ depends on both observables and unobservables and varies across worker types. We will pay special attention to the role of the total city size, N_K, on amenities across groups but could also consider the effect of other observables denoted by the vector, X_k , as well as an unobserved location amenity, B_{ik}. Assuming a log form, location-specific amenities for a given worker type are the following:

$$\ln \widetilde{B}_{ik} = \gamma_i^N \ln N_k + \gamma_i^X X_k + \ln B_{ik}.$$

3.2 Firms and Labor Demand

3.2.1 Production

A large number of small competitive firms with fixed expenditures are characterized by the production of a good of type $j \in \{1, J\}$. The goods are produced using a constant returns production technology that is an increasing function of different labor types, i. Total industry-wide expenditures are fixed at E_j.[6] E_{jk} represents the expenditures by each

[6]This assumption does not affect the analysis of relative market size across different labor types, industries, or locations. The important drawback from assuming that total expenditures are fixed, however, is that it

industry in each location such that

$$\sum_k E_{jk} = E_j.$$

The production technology varies across locations and industries, both in terms of total factor productivity, $\widetilde{A}_{jk}$, and the relative marginal productivity of different types of labor, $\widetilde{\beta}_{ijk}$. In addition, firms choose a single location and are subject to an idiosyncratic location-specific productivity component over different locations, denoted by $\nu_{jk,m}$, that is distributed i.i.d. and is known to the firm exante. The subscript m denotes an individual firm.[7] In addition, we will assume initially that prices are exogenously determined and goods are shipped costlessly, so that prices may be normalized and subsumed by the TFP term. Assuming a Cobb-Douglas form, we can write the profit function for a given firm in a given location as the following:

$$\pi_{jk} = \nu_{jk,m}\widetilde{A}_{jk}\prod_i n_{ijk}^{\widetilde{\beta}_{ijk}} - \sum_i n_{ijk}w_{ik},$$

where

$$\sum_i \widetilde{\beta}_{ijk} = 1, \forall j, k.$$

Note that labor markets are competitive, such that wages for a given worker type must be the same across all industries in a given location in equilibrium.

3.2.2 Industry Location

The maximization problem for each firm in each location is given by,

$$\max_{n_{ik}} \pi_{jk} = \nu_{jk,m}\widetilde{A}_{jk}\prod_i n_{ijk}^{\widetilde{\beta}_{ijk}} - \sum_i n_{ijk}w_{ik}. \tag{3}$$

prevents us from studying the effects on the total market size in this economy. A simple extension to the current research would be to include an outside option (for example capital expenditures). This could then be estimated using methods similar those introduced by Berry (1994).

[7]Note that this corresponds to an individual worker observation for empirical purposes.

Solving the maximization problem gives the indirect profit per unit expenditure as a function of wages:

$$\Psi(W_{jk}; \widetilde{A}_{jk}) = \nu_{jk,m} \widetilde{A}_{jk} W_{jk}^{-1} - 1,$$

where W_{jk} is the unit cost given by

$$W_{jk} = \prod_i \left(\frac{w_{ik}}{\widetilde{\beta}_{ijk}} \right)^{\widetilde{\beta}_{ijk}}.$$

Again, using standard discrete choice theory, we can then write the probability that a firm of a given type chooses a given location conditional on location-specific productivity and wages, using the following:

$$P_j(k|\widetilde{A}_{jk}, W_{jk}) = \frac{\exp(\ln \widetilde{A}_{jk} - \ln(W_{jk}))}{\sum\limits_k \exp(\ln \widetilde{A}_{jk} - \ln(W_{jk}))}. \tag{4}$$

The aggregate expenditures for a given industry in a given location are then given by

$$E_{jk}(\widetilde{A}_{jk}, W_{jk}) = E_j \frac{\exp(\ln \widetilde{A}_{jk} - \ln(W_{jk}))}{\sum\limits_k \exp(\ln \widetilde{A}_{jk} - \ln(W_{jk}))}.$$

3.2.3 Labor Demand Across Locations

Given expenditure shares by industry, we can now derive the labor demand for different worker types in each location. First, note that the labor demand for a given worker type in a given industry, in a given location is given by

$$N_{ijk}^D = \frac{E_{jk} \widetilde{\beta}_{ijk}}{w_{ik}}.$$

Aggregate labor demand for each worker type in a location is given by summing over all industries.

$$N_{ik}^D = \frac{1}{w_{ik}} \sum_j E_{jk} \widetilde{\beta}_{ijk}.$$

Given that this expression is a sum over the nonlinear expenditure functions, $E_{jk}(\widetilde{A}_{jk}, W_{jk})$, for each location, further analytical simplification is difficult. The demand elasticity for different types of labor will depend on the relative wages as well as on the composition of industries. Nonetheless, for given model parameters, the demand functions are easily calculated.

Finally, as with amenities, we want to further decompose the relative production advantages of different locations. We will assume that both location-specific TFP and labor-specific technology are dependent, at least partially, on observables. For the TFP term $\widetilde{A}_{jk}$, we will assume the following form:

$$\ln \widetilde{A}_{jk} = \eta_j^N \ln N_k + \eta_j^X X_k + A_k,$$

where N_k is the city size, X_k is a vector of other observables, and A_k is some unobserved component of productivity.

For the labor-specific productivity, $\widetilde{\beta}_{ijk}$, we want to separate the industry links from skill-biased location advantages. To do this, we assume the labor-specific productivity, y_{ijk}, is given by the following:

$$y_{ijk} = \phi_{ij,m} \beta_{ij} \widetilde{\alpha}_{ijk}.$$

Here, β_{ij} represents the industry-specific labor technology, $\widetilde{\alpha}_{ijk}$ represents the location-specific labor technology, and $\phi_{i,m}$ is an idiosyncratic labor-specific productivity shock distributed i.i.d. Then, taking the expectation and aggregating, the share of labor expenditures in a given location by a given industry is given by

$$E[\widetilde{\beta}_{ijk}] = P_{jk}(i|\beta_{ij}, \widetilde{\alpha}_{ijk}) = \frac{\exp(\ln \beta_{ij} + \ln \widetilde{\alpha}_{ijk})}{\sum_i \exp(\ln \beta_{ij} + \ln \widetilde{\alpha}_{ijk})}.$$

We also will assume that $\widetilde{\alpha}_{ijk}$ is partially dependent on observables and is given by

$$\ln \widetilde{\alpha}_{ijk} = \chi_{ij}^{N} \ln N_k + \chi_{ij}^{X} X_k + \alpha_{ijk},$$

where, again, N_k is the city size, X_k is a vector of other observables, and α_{ijk} is unobserved.

3.3 The Housing Market

To close the model and to pin down the city size distribution, we need to define the housing market for each location. Housing demand for a given worker type in a given location is given by

$$l_{ik} = \tfrac{\theta}{r_k} w_{ik}.$$

Therefore, aggregate housing demand in a given location is given by

$$L_k^D = \tfrac{\theta}{r_k} \sum_i N_{ik}^S w_{ik} \ .$$

To model the housing supply, we assume that rents are collected by an absentee landlord who supplies housing in each location based on the following supply function:

$$L_k^S = C_k r_k^{\delta_k}.$$

Here, C_k and δ_k are scale and elasticity parameters, respectively, and can vary by location.

3.4 Equilibrium

Equilibrium is defined as a set of wages for each location and worker type $\{w_{ik}\}$*, a set of rents for each location* $\{r_k\}$*, a distribution of worker types across locations* $\{N_{ik}\}$*, and a distribution of land consumption across locations* $\{L_k\}$*, such that:*

1. *In each location, workers maximize utility subject to their budget constraints (equation (1)).*

2. *In each location, firms maximize profits (equation (3)).*

3. *Workers choose the location that maximizes utility (in expectation, this is given by equation (2)).*

4. *Firms choose the location that maximizes profits (in expectation, this is given by equation (4)).*

5. *Labor markets clear for each worker type in each location,* $N_{ik}^S = N_{ik}^D$.

6. *Housing markets clear in each location,* $L_k^S = L_k^D$.

4 Estimation

This section outlines the estimation strategy to recover all of the parameters of the model. The estimation method follows standard discrete choice simulation and estimation methods to recover all of the amenity and production parameters. The parameters can all be estimated by maximizing the likelihood functions using standard computational techniques.

Note that the basic estimation strategy is to identify technology and preference parameters by observing how quantities of workers and expenditures change across space while conditioning on prices. This is the standard method for demand analysis; the difference here is that labor prices are different for different workers and firms, and this must be accounted for correctly in the logit function.

It is important to consider the following regarding the interpretation of all of the supply and demand parameters. In general, the estimates for different skill groups or industries should be interpreted relative to one another and not in absolute terms. In theory, the absolute levels of the estimates have a real world interpretation, but there is an omitted variable bias in the sense that any variable correlated with amenities or productivity that is also correlated with city size will lead to a bias that overstates the importance of city size. However, the relative estimates are unbiased if unobserved city characteristics are valued the same across skill groups. In effect, differencing across skill groups removes the bias if other preference parameters on unobservables are the same. On the other hand, this is only an issue if we are trying to understand the causal effect of city size, as is common in the literature on agglomeration. Arguably, it makes sense to first understand the relative value of big cities for different skill groups, regardless of whether that value is coming from city size itself or other innate features such as good weather, natural resources, or natural transportation hubs. These variables can be added as controls later.

4.1 Wages

Before estimating the supply and demand equations, we first need to measure prices. Wages are estimated by taking the mean of all log wages in a given location for a given worker type:

$$\widehat{w}_{ik} = \frac{1}{N_{ik}} \sum_{m} d_{ik,m} w_m,$$

where $d_{ik,m}$ is a location/worker type dummy.

4.2 Rents

Rents are estimated for each MSA using a hedonic regression of house prices on housing characteristics following the method used by Chen and Rosenthal (2008) to control for differences in housing stock across cities. We run the following regression on log rents:

$$\ln r_m = \lambda_0 + \lambda_k d_k + \lambda_X X_m + \epsilon_m,$$

where r_m is the observed rent of a housing unit, d_k is a location dummy, and X_m is a vector of observed housing characteristics. The estimate for rents in each location is then recovered using the sample averages for housing characteristics, $\bar{X}$:

$$\widehat{r}_k = exp(\widehat{\lambda}_0 + \widehat{\lambda}_k + \widehat{\lambda}_X \bar{X}).$$

4.3 Skill-Specific Preferences

To estimate the preference parameters, we need to first estimate the housing share of consumption, θ. To do this, we will assume that this is constant across worker types and locations and simply calculate the average rent per unit wage, which is 0.26 in the year 2000 data.[8]

Using maximum likelihood, we can estimate the vector $\gamma_i = [\gamma_i^N \ \gamma_i^X]$. The log-likelihood function is given by

$$\mathcal{L}(\gamma_i) = \tfrac{1}{N_i} \sum_k \sum_m d_{ik,m} \ln P_i^S(k|\widetilde{B}_{ik}, w_{ik}, r_k).$$

We can aggregate to get the following estimator:

$$\widehat{\gamma}_i = \arg\max_{\gamma_i} \sum_k \tfrac{N_{ik}}{N_i} \ln P_i^S(k|\widetilde{B}_{ik}, w_{ik}, r_k).$$

4.4 Industry-Specific Productivity

In a similar manner to the estimation of amenities, we estimate the industry-specific productivity parameter vector $\eta_j = [\eta_j^N \ \eta_j^X]$. The log-likelihood function is given by:

$$\mathcal{L}(\eta_j) = \tfrac{1}{E_j} \sum_k \sum_m d_{jk,m} w_m \ln P_j(k|\widetilde{A}_{jk}, W_{jk}),$$

where $d_{jk,m}$ is a industry/location dummy. We can aggregate to get the following estimator:

$$\widehat{\eta}_j = \arg\max_{\eta_j} \sum_k \tfrac{E_{jk}}{E_j} \ln P_j(k|\widetilde{A}_{jk}, W_{jk}).$$

4.5 Worker-Specific Productivity

Next, we estimate the worker-specific productivity parameter vector, $\chi_{ij} = [\chi_{ij}^N \ \chi_{ij}^X \ ]$, and the industry/occupation share parameter, β_{ij}, simultaneously. The log-likelihood function is given by

[8] This is consistent with housing expenditure estimates. See Davis and Ortalo-Magne (2011) for a detailed discussion of housing expenditures over time and across cities.

$$\mathcal{L}(\chi_{ij}, \beta_{ij}) = \sum_i \sum_j \sum_k \sum_m d_{ijk,m} w_m \ln P_{jk}(i|\beta_{ij}, \widetilde{\alpha}_{ijk}),$$

where $d_{ijk,m}$ is an education/industry/location dummy. We can aggregate to get the following estimator:

$$[\widehat{\chi}_{ij} \ \ \widehat{\beta}_{ij}] = \underset{\chi_{ij}, \beta_{ij}}{\arg\max} \sum_i \sum_j \sum_k \frac{E_{ijk}}{E_{jk}} \ln P_{jk}(i|\beta_{ij}, \widetilde{\alpha}_{ijk}).$$

4.6 Housing Supply

For simplicity, we will assume a housing supply elasticity of 5.0 for all locations.[9] The scale parameter of the housing supply function can then be backed out from the rents, total employment, and wages in each location, by assuming market clearing for housing:

$$L_k^S = L_k^D = \frac{\theta}{r_k} \sum_i N_{ik}^S w_{ik},$$

$$\widehat{C}_k = \frac{L_k^S}{\widehat{r}_k^{\delta_k}}.$$

5 Quantitative Results

This section presents the results of the estimation as well as additional quantitative analysis in order to quantify and decompose the various sources driving the spatial distribution of worker types.[10] The primary focus here will be to explain the relative value of city size for both production and consumption across skill groups. However, some other interesting results are discussed as well.

[9] Green, Malpezzi, and Mayo. (2005) provide estimates for the price elasticity of housing across metro areas and do not find that elasticities are strongly correlated with population.

[10] Most of the parameter estimates are contained in this section; however, to avoid information overload, some are located in Appendix A. These include the estimates of industry-specific labor technology, β_{ij}, which, while important, are difficult to interpret and contain little information that cannot be gleaned from Table 1, which shows skill group shares by industry. Also contained in the appendix are the estimates of the housing supply scale parameters, C_k, and the estimated monthly rents, r_k, for 2010. These roughly capture the relative supply across cities that is found in the literature. Estimates of the parameters χ_{ij}, β_{ij}, and C_k for 1980, 1990, and 2000 are not included but are available upon request.

5.1 Parameter Estimates

First, we will consider the relationship between city size and consumption amenities, and how that relationship has changed over time. Table 3 shows the parameter estimates for the amenity value of city size across different skill groups, γ_i^N, for each decade from 1980 to 2010. These parameter estimates should be interpreted as the percentage increase in a skill group population for a 1 percent increase in total population, holding prices constant. Therefore, a value above 1 represents increasing relative labor supply with city size, and a value below 1 represents decreasing relative labor supply with city size.

In the cross section, for all years, there is generally a positive correlation with the relative amenity value of city size and skill level. The exception is for those workers without high school degrees, who also place high value on big city amenities. Over time, the value of urban amenities has increased among highly educated workers relative to workers with lower education levels. Again, the exception is among those workers without a high school education. What these estimates suggest is that urban amenities are at least partially responsible for the increased sorting of high-skilled individuals into large cities.

Table 3: Estimates of City Size Effect on Labor Supply by Education Level, (γ_i^N)

Education Level	1980	1990	2000	2010	Change 1980-2010
< High School	0.9824	1.0261	1.0466	1.1076	0.1252
High School	0.9437	0.95	0.9382	0.9461	0.0024
Some College	0.9732	0.9551	0.9429	0.9461	-0.0271
College	1.0151	1.067	1.068	1.0667	0.0516
Graduate School	1.0508	1.1038	1.1126	1.1034	0.0526
College - H.S.*	0.0714	0.117	0.1298	0.1206	0.0492

Estimates represent relative preference parameters for city size (γ_i^N) for different education levels. A value of 1 represents proportional growth for a skill group with respect to city size, holding prices constant. *College - H.S. is the difference in the parameter estimates between the college group and the high school group.

Next, we consider the relationship between productivity and city size across industries. Table 4 shows the estimates of η_j^N, which represent the percentage change in expenditures for a 1 percent increase in total city employment for each industry from 1980 to 2010, holding labor costs fixed. These estimates clearly show that some industries derive much greater productivity value from large cities than others. The highest estimates come from finance, professional services, and legal services, which are notably all high-skilled industries. The lowest estimates are for agriculture, utilities, and durable goods, which are lower-skilled industries. However, this correlation does not hold for all industries. For example, health care and education, both high-skilled industries, display relatively low productivity returns to city size.

If we look across time, the estimates are very persistent across industries. In addition, there do not seem to be systematic changes within industries in the productivity returns to city size. Some of the estimates have increased and some have decreased, and there is no obvious correlation with either relative skills or industry size.

Table 4: Relative Productivity Returns of City Size by Industry for 1980 to 2010

Industry	1980	1990	2000	2010	Change 1980-2010
Retail Trade	0.946	0.9304	0.9303	0.9361	-0.0099
Education	0.9607	0.961	0.9869	0.998	0.0373
Health Care	1.0064	0.9899	0.997	0.9848	-0.0216
Durable Goods	0.955	0.9195	0.8708	0.8801	-0.0749
Finance, Insurance and Real Estate	1.07	1.0988	1.1226	1.1239	0.0539
Business and Repair Services	1.071	1.0671	1.099	1.0709	-0.0001
Construction	0.8748	0.9458	0.9246	0.9629	0.0881
Nondurable Goods	0.9805	0.9666	0.9674	0.974	-0.0065
Public Administration	0.9525	0.9554	0.948	0.968	0.0155
Transportation	1.0439	1.0423	1.0439	1.0291	-0.0148
Social Services	1.0198	1.0034	1.026	1.0126	-0.0072
Professional Services	1.1237	1.1308	1.1816	1.1674	0.0437
Personal Services	0.9218	0.95	1.0138	1.0375	0.1157
Wholesale Durable Goods	0.9893	1.0037	0.9888	0.9481	-0.0412
Agriculture, Forestry and Fisheries	0.5813	0.6904	0.7151	0.7373	0.1560
Wholesale Nondurable Goods	1.0104	1.0147	1.0138	1.0144	0.0040
Communications	0.9919	1.0405	1.0989	1.0754	0.0835
Entertainment and Recreation	1.0826	1.0884	1.0308	1.0489	-0.0337
Legal Services	1.1595	1.1753	1.2471	1.2795	0.1200
Utilities and Sanitary Services	0.9045	0.894	0.8721	0.8261	-0.078

Estimates represent relative productivity parameters (η_j^N) for city size for different industries. A value of 1 represents proportional growth for an industry with respect to city size, holding prices constant.

Table 5 shows the estimates of χ_{ij}, which represent the skill-specific shifts in expenditures within each industry as total city employment increases. Note that the omitted category is "< high school," which is normalized to 0. The most striking feature of these results is that for every industry, expenditures are shifted to high-skilled labor in larger cities. This is consistent with previous research that has suggested that tasks and skills are important drivers of productivity in cities. Also note that not all industries adjust employment as readily. In particular, education and health care are two of the least responsive industries in adjusting skilled labor expenditure shares with city size. This suggests that there are two ways in which industry composition can affect skill composition, through differences in average skill share or through differences in how the skilled labor share changes across locations.

Table 5: Industry/Education Production Returns to City Size (χ_{ij}) for 2010

	High School	Some College	College	Graduate School
Retail Trade	-0.1013	-0.0266	0.1372	0.2372
Education	-0.1311	-0.0922	-0.0489	-0.0174
Health Care	-0.0436	-0.0544	0.1089	0.1376
Durable Goods	-0.0742	0.0457	0.241	0.3523
Finance, Insurance and Real Estate	-0.1237	-0.0311	0.1208	0.2854
Business and Repair Services	-0.1944	-0.0944	0.1637	0.3334
Construction	-0.1498	-0.0896	0.0634	0.1404
Nondurable Goods	-0.0513	-0.0182	0.196	0.3452
Public Administration	-0.0152	0.0267	0.1222	0.2198
Transportation	-0.0715	0.0451	0.2375	0.2533
Social Services	0.0126	0.0712	0.1353	0.1681
Professional Services	-0.0033	0.0086	0.2124	0.344
Personal Services	-0.1686	-0.1149	0.111	0.1828
Wholesale Durable Goods	-0.1897	-0.0412	0.0884	0.1168
Agriculture, Forestry and Fisheries	-0.2054	-0.1894	-0.0182	0.1506
Wholesale Nondurable Goods	-0.0669	0.056	0.1745	0.4353
Communications	-0.259	-0.1134	0.0609	0.2252
Entertainment and Recreation	0.0583	0.1864	0.3985	0.5018
Legal Services	0.3619	0.5295	0.6922	0.8149
Utilities and Sanitary Services	-0.2056	-0.1489	0.0243	0.0965

The estimates represent industry/worker type-specific returns to city size (χ_{ij}). χ_{1j} is normalized to 0 for all j (i.e. the "< high school" category is omitted).

5.2 Decomposing Demand

While we are able to encapsulate the response in labor supply into a single parameter for each worker type (Table 3), an equivalent representation for labor demand by skill group is not as simple. The reason for the complexity is that labor demand across skill types is derived by aggregating across all industries and therefore depends on the composition of industries in the economy as a whole and in each city. This aggregation introduces nonlinearities in the response of skill demand to city size, thus making the marginal demand with respect to city size dependent on city size itself. The entire predicted demand curve can be calculated, but it is not very useful for comparison.

Nonetheless, we want to be able to compare the response of labor demand with the response of labor supply. Therefore, the strategy taken here is to calculate the marginal response of labor demand to city size for a representative city. We choose the representative city to have a total employment of 1 million workers. This employment number corresponds approximately to the employment of the city in which the median U.S. worker lives i.e., half of the workers live in smaller cities and half live in larger cities. For reference, this is right around the employment of the Denver, Tampa, and Pittsburgh metro areas.

To calculate the aggregate labor supply, we first set the prices equal to the average prices for each skill group in the entire economy. Then, the marginal response of labor demand for each worker type can be calculated numerically using all of the estimated firm technology parameters. First, we present the results by allowing for all responses to changes in city size, including both the changes in industry expenditures with respect to city size through total factor productivity shifts and the changes in skill-specific demand within industries. Then we shut down the effect of various parameters to decompose the source of skilled-labor demand. Finally, we analyze the changes in labor demand over time and also consider the role of aggregate industry composition changes.

Table 6 shows the demand response of city size for each skill group in each decade, allowing for both industry-specific and skill-specific effects. Similar to the results for labor supply shown in Table 3, the numbers represent the predicted percentage change in labor supply in each group for a 1 percent change in aggregate city employment, holding prices constant. For all years, there is clearly a stronger relative response in the demand for high-skilled workers as city size increases. Furthermore, this response has strengthened over time, with the gap between college graduates and others increasing between 1980 and 2010.

For all years, the relative demand response is larger than the supply response, which would be expected given the increasing wage gap with city size. However, the magnitude of both supply and demand responses are economically significant. For example, compare the difference in demand between college graduates and high school graduates in 2010, 0.227, with the difference in supply, 0.121 (from Table 3). Also note that the change in the relative supply versus demand between 1980 and 2010 is of similar magnitude. Again, comparing college graduates with high school graduates, the change in the difference in supply across groups versus the difference in demand shows that both are of similar magnitude (0.0492 versus 0.1002 respectively); however, the demand elasticity due to increases in productivity dominates.

Table 6: City Size Effect on Labor Demand by Skill Level

Education Level	1980	1990	2000	2010	Change 1980-2010	Change (Normalized*)
< High School	0.9511	0.9211	0.9183	0.9879	0.0368	0.0123
High School	0.9469	0.9091	0.9038	0.8836	-0.0633	-0.0899
Some College	1.0209	0.9941	0.9859	0.9535	-0.0674	-0.0780
College	1.0737	1.0982	1.122	1.1106	0.0369	0.0292
Graduate School	1.093	1.1142	1.1537	1.1478	0.0548	0.0468
College - H.S.**	0.1268	0.1891	0.2182	0.227	0.1002	0.1190

The results represent predicted demand for different skill levels, accounting for both industry-specific and skill-specific components. A value of 1 represents proportional demand growth for a skill group with respect to city size, holding prices constant. *The normalized results control for exogenous industry composition changes over time. **College - H.S. is the difference in the parameter estimates between the college group and the high school group.

Next, we want to decompose the contributions of technology in labor demand across cities into those related to industry-specific productivity versus those related to skill-specific productivity. The industry-specific component of relative skill demand comes from differential changes in total factor productivity with respect to city size across industries that have different skilled labor shares. More simply, the industry-specific component is that which arises through the parameters, η_j^N. If industries with higher average skill levels are systematically overrepresented in cities, then we would expect this to increase demand for high-skilled labor. This is implemented using average labor shares for each industry and assuming that they do not change with city size, effectively "turning off" the effect of χ_{ij} and then recalculating the labor demand response.

Likewise, the skill-specific component of relative skill demand comes from changes within industries in labor shares in larger cities. In other words, the skill-specific component is that which arises through the parameters χ_{ij}. This is calculated by fixing industry-specific total factor productivity and recalculating the demand response. Note that "skill-specific component" as it is used here is a bit of a misnomer, given that we allow the parameters χ_{ij} to vary freely across industries meaning the skill-specific response can also vary across industries. Later, we will explore the relative contributions of industries.

Tables 7 and 8 show the results for the industry-specific and skill-specific components, respectively. The first thing to note is that in the cross section, differences in relative skilled labor demand are driven mostly by skill-specific productivity differences, but there is a small effect from industry-specific factors. In 2010, comparing high school and college graduates, the skill-specific component accounts for a difference of 0.1979 between demand increases for college versus high school graduates, while the difference arising from the industry-specific component is only 0.0292. This suggests that the driving force behind the sorting of skill types across cities arises from skill-specific production advantages of large cities, although differences in industry-specific productivity does contribute positively to skilled demand due to changes in industry composition in large cities.

Likewise, when we consider the changes over time, skill-specific components dominate. For example, the change due to the industry-specific component between 1980 and 2010 in the relative demand between college and high school graduates is only 0.0157. The same value for the skill-specific component is 0.0844. Finally, we want to consider the role of changes in economy-wide industry composition over time. The final columns in Tables

6, 7, and 8 recalculate the changes over time by removing the component that is related to changes in industry composition. This is done by fixing industry expenditure shares at 1980 levels, but allowing changes in technology. Again, subtracting the changes for college versus high school demand, we actually find a larger difference for the total effect of 0.1191, suggesting that industry composition has actually worked against relative demand for high-skilled labor in cities over time. The results also suggest that changes in industry composition have increased industry-specific effects but have worked against skill-specific technology effects.

Table 7: City Size Effect on Labor Demand by Skill Level: Industry-Specific Component

Education Level	1980	1990	2000	2010	Change 1980-2010	Change (Normalized*)
< High School	0.9617	0.9579	0.9563	0.9593	-0.0024	-0.0146
High School	0.9747	0.9749	0.9804	0.9835	0.0088	-0.0068
Some College	0.9829	0.9861	0.9959	0.9958	0.0129	-0.0023
College	0.9882	0.9957	1.0124	1.0127	0.0245	0.0041
Graduate School	0.9908	0.9995	1.0193	1.0196	0.0288	0.0085
College - H.S.**	0.0135	0.0208	0.032	0.0292	0.0157	0.01084

The results represent predicted demand for different skill levels, accounting for only industry-specific returns (η_j^N) and not the skill-specific component within industries. A value of 1 represents proportional demand growth for a skill group with respect to city size, holding prices constant. *The normalized results control for exogenous industry composition changes over time. **College - H.S. is the difference in the parameter estimates between the college group and the high school group.

Although we have established that relative increases in skilled-labor demand in cities are driven primarily by skill-specific technology changes within industries, this does not suggest that in the cross section or over time these skill-specific changes are equal across industries. Table 9 shows the main components that affect skilled labor demand in cities for 1980 and 2010, along with the total contribution of each industry to changes in skill demand in cities over that time. This table is meant to summarize which industries are the largest contributors to demand for skilled labor in large cities and illuminate the underlying components of this contribution.

There are four main components that make up the industry contribution to skilled-labor demand in cities. The first is the size of the industry in general, which we calculate as the

Table 8: City Size Effects on Labor Demand by Skill Level: Skill-Specific Component

Education Level	1980	1990	2000	2010	Change 1980-2010	Change (Normalized*)
< High School	0.9893	0.9634	0.9622	1.0285	0.0392	0.0271
High School	0.9724	0.9342	0.9232	0.8995	-0.0729	-0.0835
Some College	1.0384	1.0079	0.9898	0.9571	-0.0813	-0.0765
College	1.0859	1.1026	1.1095	1.0974	0.0115	0.0240
Graduate School	1.1025	1.1147	1.1345	1.128	0.0255	0.0373
College - H.S.**	0.1135	0.1684	0.1863	0.1979	0.0844	0.1075

The results represent predicted demand for different skill levels, accounting for only skill-specific returns (χ_{ij}) within industries and not industry-specific returns. A value of 1 represents proportional demand growth for a skill group with respect to city size, holding prices constant. *The normalized results control for exogenous industry composition changes over time. **College - H.S. is the difference in the parameter estimates between the college group and the high school group.

share of the total economy, measured by total labor expenditures. The second component is the change in industry expenditures with respect to city size, given by the estimates of η_j. The third component is the change within industries in skilled-labor demand with respect to city size, which is calculated as the difference in change in demand for college versus high school graduates, or $\chi_{4j} - \chi_{2j}$. The final component is the average expenditure share on skilled labor for each industry. This is calculated as the share of labor expenditures on workers with college or graduate degrees. The last column represents the industry contribution to the changes in skilled-labor demand in cities between 1980 and 2010, as a percentage of the total. The total change in skilled-labor demand for college graduates versus high school graduates over the time period is 0.1002.[11]

The most striking result is that demand for skilled labor in cities has increased within every industry, which suggests that there has been an important technological change that is partially independent of industry characteristics. This can be seen by comparing city/skill demand in 1980 with 2010 in Table 9. However, note that not all industries changed in

[11] To be precise, the last column is calculated by first calculating the contribution of each industry to relative increase in demand for college graduates versus high school graduates for a 1 percent increase in city size for both 1980 and 2010. This number is then differenced for each industry to get the change in contribution over time. Finally, this is divided by the total change between 1980 and 2010 in the elasticity of demand for college graduates versus high school graduates with respect to city size.

the same way. Health care, for example, has a relatively stable skill mix across locations, and this has changed only slightly over the time period. The finance industry, on the other hand, changed from having relatively low variation in skill mix across cities to the highest of any industry in 2010.

This partially explains why finance is the largest contributor to the change in skill demand in large cities over time, accounting for 35 percent of the change between 1980 and 2010. Additionally, the finance industry had disproportionate gains in industry size, productivity returns to city size, and skilled labor share. Another big contributor to demand changes at 28.5 percent of the total was the business services sector. However, this was due mostly to the fact that the industry doubled in size and changed its overall skill share, as opposed to technology changes within the industry related to the productivity of large cities. Some industries actually contributed negatively to skill demand in cities, the largest being the construction industry. This was due to relatively meager gains in skill demand, both overall and in large cities, compared with other industries, along with a small decline in overall industry size.

6 Conclusion

This paper develops and estimates a model of location choice to account for heterogeneity in productivity and preferences across different worker types with regard to the amenities offered in large cities. By doing this, we are able to isolate the various components leading to the overrepresentation of high-skilled workers in large cities. We find that both supply and demand for high-skilled workers increase relative to low-skilled workers in cities. However, demand for high-skilled workers increases faster with city size relative to supply, leading to upward pressure on wages for high-skilled workers relative to low-skilled workers in large cities.

We also decompose demand for skilled workers for different industries. The share of employment in different industries changes systematically as cities grow. We find that

Table 9: Industry Composition, Industry Technology and the Contribution to Changes in Skilled-labor Demand in Cities Between 1980 and 2010

	1980				2010				
	ind. size*	η_j	city/skill demand**	skilled share***	ind. size*	η_j	city/skill demand**	skilled share***	industry effect****
Retail Trade	10.52	0.946	0.1076	0.16	10.55	0.936	0.2387	0.30	-12.06
Education	7.49	0.961	-0.0373	0.73	9.09	0.998	0.0822	0.80	-10.09
Health Care	6.82	1.006	0.1406	0.43	12.43	0.985	0.1526	0.61	17.76
Durable Goods	18.12	0.955	0.1807	0.21	8.29	0.880	0.3153	0.51	25.70
Finance	7.28	1.070	0.0844	0.37	9.97	1.124	0.2447	0.66	35.23
Business Serv.	3.37	1.071	0.2706	0.26	6.78	1.071	0.3583	0.55	28.50
Construction	5.96	0.875	0.1237	0.14	5.08	0.963	0.2134	0.23	-16.17
Nondurables	8.73	0.981	0.1569	0.25	4.63	0.974	0.2474	0.52	0.75
Public Admin	6.82	0.953	0.0789	0.37	6.65	0.968	0.1374	0.54	2.62
Transport.	6.18	1.044	0.1834	0.12	4.15	1.029	0.3092	0.27	8.41
Social Serv.	1.59	1.020	0.0286	0.46	3.05	1.013	0.1228	0.57	1.12
Prof. Serv.	2.58	1.124	0.1324	0.62	5.58	1.167	0.2157	0.78	20.19
Personal Serv.	1.43	0.922	0.1471	0.11	1.79	1.038	0.2798	0.32	-0.84
Wholesale Dur.	3.15	0.989	0.1827	0.26	1.79	0.948	0.2782	0.45	-8.60
Agriculture	1.59	0.581	0.1832	0.30	1.43	0.737	0.1872	0.36	-8.97
Wholesale N.D.	2.54	1.010	0.1904	0.26	1.72	1.014	0.2416	0.47	-4.86
Comm.	2.31	0.992	0.1874	0.20	2.01	1.075	0.3201	0.56	16.82
Entertainment	0.81	1.083	0.1682	0.28	1.1	1.049	0.3404	0.44	0.37
Legal Serv.	0.89	1.160	0.164	0.68	2.35	1.280	0.3305	0.83	2.71
Utilities	1.8	0.904	0.1334	0.21	1.56	0.826	0.23	0.40	1.40

* Industry size is the share of the total economy for that industry as measured by labor expenditures.
** City/skill demand is the difference in the percentage change in demand between college graduates and high school graduates as city size increases 1 percent for each industry.
*** Skilled Share is the share of total labor expenditures on high skilled labor (college degree or higher) within each industry.
**** Industry effect is the contribution from each industry toward the change between 1980 and 2010 in relative skilled labor demand in large cities as a percentage of the total change. The total change in skilled-labor demand for college graduates versus high school graduates is 0.1002.

changes in industry composition result in some increased demand for skilled workers in large cities but do not account for the change over time in this relative demand. Instead, within-industry changes in skilled-labor shares drive increased demand for educated workers in cities. All industries shift some resources from low-skilled to high-skilled labor in large cities, and over time, high-skilled workers within all industries have become more concentrated in large cities.

Interestingly, however, not all industries exhibit the same flexibility in adjusting their workforce across cities. For example, health care and education, two industries that have grown significantly, maintain a relatively uniform workforce composition across cities, and this has not changed very much over time. On the other hand, the finance and professional service industries, which also have grown, have been able to increasingly concentrate their high-skilled workers into large cities. This suggests that while there was some technological change that affected all industries, certain industries have a greater ability to sort workers across space. This flexibility is not obviously related to average skill levels, tradability of the sector, or even industry growth. As the composition of industries continues to evolve, it becomes increasingly important to understand the relationship between cities, industries, and skills, given that there may be important implications, not only for efficiency, but also inequality.

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Appendix

A Additional Parameter Estimates

Table 10: Industry/Education Production Parameter Estimates (β_{ij}) for 2010

	High School	Some College	College	Graduate School
Retail Trade	3.9493	2.71	0.285	-2.3199
Education	4.9231	4.5073	4.9628	5.1626
Health Care	3.8383	4.6352	2.3585	2.475
Durable Goods	3.7769	1.9704	-0.342	-2.3691
Finance, Insurance, and Real Estate	5.5536	4.546	3.1424	0.1094
Business and Repair Services	5.2076	3.8336	0.7238	-2.4305
Construction	4.3214	2.9858	0.6146	-1.6989
Nondurable Goods	3.3301	2.5241	0.0924	-2.5281
Public Administration	4.4529	4.3135	3.0658	1.3782
Transportation	3.9859	2.1036	-0.8162	-2.4202
Social Services	2.7765	2.1358	1.579	0.9357
Professional Services	3.8182	4.1154	2.4612	0.2669
Personal Services	4.6048	3.6636	0.4372	-1.643
Wholesale Durable Goods	5.5237	3.4017	1.8939	0.3237
Agriculture, Forestry and Fisheries	4.3527	3.5834	1.2787	-1.1648
Wholesale Nondurable Goods	3.6004	1.6757	0.5338	-4.2177
Communications	7.5704	5.9478	3.7052	0.4949
Entertainment and Recreation	2.1191	0.4623	-2.3656	-5.2507
Legal Services	0.0217	-1.7825	-4.1151	-3.9421
Utilities and Sanitary Services	5.9187	4.9254	2.6325	0.9436

Estimates represent industry-specific production parameters (β_{ij}) over different worker types. β_{1j} is normalized to 1 for all j i.e., the $<$ high school category is omitted.

Table 11: Housing Supply Parameters for Each MSA (C_k), and Rents (r_k) in Dollars per Month, for 2010

MSA	C_k	r_k ($)
Abilene, TX	1.59	691
Akron, OH	5.87	761
Albany-Schenectady-Troy, NY	1.27	1037
Albuquerque, NM	2.33	913
Alexandria, LA	1.56	686
Allentown-Bethlehem-Easton, PA/NJ	1.05	1019
Altoona, PA	3.38	610
Amarillo, TX	3.31	690
Anchorage, AK	0.10	1356
Ann Arbor, MI	2.00	898
Anniston, AL	6.86	520
Appleton-Oshkosh-Neenah, WI	2.05	829
Atlanta, GA	17.16	898
Atlantic City, NJ	0.11	1342
Augusta-Aiken, GA-SC	6.34	696
Austin, TX	2.11	1073
Bakersfield, CA	2.32	866
Baltimore, MD	1.17	1311
Baton Rouge, LA	3.27	848
Beaumont-Port Arthur-Orange, TX	10.17	604
Bellingham, WA	0.06	1311
Benton Harbor, MI	1.80	700
Billings, MT	0.88	809
Biloxi-Gulfport, MS	1.94	779
Binghamton, NY	4.15	658
Birmingham, AL	4.49	827
Bloomington-Normal, IL	1.71	756
Boise City, ID	2.57	833
Boston, MA-NH	0.28	1820
Bremerton, WA	0.08	1317
Bridgeport, CT	0.03	1673
Brownsville-Harlingen-San Benito, TX	18.34	513
Buffalo-Niagara Falls, NY	14.69	703
Canton, OH	5.53	679
Cedar Rapids, IA	2.69	729
Champaign-Urbana-Rantoul, IL	0.83	853
Charleston-N. Charleston, SC	0.63	1054
Charlotte-Gastonia-Rock Hill, NC-SC	7.23	881
Chattanooga, TN/GA	3.10	783
Chicago, IL	4.58	1255
Chico, CA	0.12	1126
Cincinnati-Hamilton, OH/KY/IN	7.61	840
Cleveland, OH	14.29	793
Colorado Springs, CO	1.09	980
Columbia, MO	1.19	774
Columbia, SC	4.27	784
Columbus, OH	7.65	856
Corpus Christi, TX	3.01	716
Dallas-Fort Worth, TX	25.73	877
Danville, VA	4.60	542
Davenport, IA-Rock Island-Moline, IL	2.48	749
Daytona Beach, FL	1.57	849
Dayton-Springfield, OH	10.28	706
Decatur, IL	4.29	566
Denver-Boulder, CO	2.22	1157

MSA	C_k	r_k ($)
Longview-Marshall, TX	3.23	651
Los Angeles-Long Beach, CA	0.29	2060
Louisville, KY/IN	5.80	802
Lubbock, TX	2.46	726
Macon-Warner Robins, GA	5.46	664
Madison, WI	0.40	1174
Manchester, NH	0.04	1304
Mansfield, OH	3.32	602
McAllen-Edinburg-Pharr-Mission, TX	38.12	513
Medford, OR	0.12	1124
Melbourne-Titusville-Cocoa-Palm Bay, FL	2.60	828
Memphis, TN/AR/MS	7.50	780
Miami-Hialeah, FL	0.66	1315
Milwaukee, WI	1.85	1071
Minneapolis-St. Paul, MN	3.66	1113
Mobile, AL	4.94	744
Modesto, CA	0.69	992
Monroe, LA	4.81	596
Montgomery, AL	4.49	700
Muncie, IN	3.19	593
Nashville, TN	3.47	951
New Bedford, MA	0.06	1271
New Haven-Meriden, CT	0.07	1485
New Orleans, LA	2.10	967
New York-Northeastern NJ	0.65	1985
Norfolk-VA Beach-Newport News, VA	0.85	1213
Ocala, FL	2.52	706
Odessa, TX	3.75	695
Oklahoma City, OK	8.40	753
Olympia, WA	0.19	1143
Omaha, NE/IA	5.04	789
Orlando, FL	5.12	925
Pensacola, FL	1.72	831
Peoria, IL	3.71	740
Philadelphia, PA/NJ	3.69	1195
Phoenix, AZ	7.03	981
Pittsburgh, PA	27.98	717
Portland, OR-WA	0.94	1255
Providence-Fall River-Pawtucket, MA/RI	0.43	1252
Provo-Orem, UT	1.52	868
Pueblo, CO	1.49	700
Racine, WI	0.42	954
Raleigh-Durham, NC	3.62	976
Reading, PA	1.25	897
Redding, CA	0.13	1069
Reno, NV	0.52	1050
Richland-Kennewick-Pasco, WA	1.09	847
Richmond-Petersburg, VA	1.15	1114
Riverside-San Bernardino, CA	3.26	1094
Roanoke, VA	0.58	946
Rochester, NY	8.99	762
Rockford, IL	3.20	728
Sacramento, CA	0.64	1305
Saginaw-Bay City-Midland, MI	13.07	585
Salem, OR	0.45	973

Table 12: Housing Supply Parameters for Each MSA (C_k), and Rents (r_k) in Dollars Per Month, for 2010 (Continued)

MSA	C_k	r_k (\$)	MSA	C_k	r_k (\$)
Des Moines, IA	2.31	842	Salinas-Sea Side-Monterey, CA	0.01	1827
Detroit, MI	57.76	700	Salt Lake City-Ogden, UT	2.93	974
Duluth-Superior, MN/WI	1.39	775	San Antonio, TX	12.07	787
Eau Claire, WI	1.07	775	San Diego, CA	0.15	1826
El Paso, TX	12.01	640	San Francisco-Oakland-Vallejo, CA	0.09	2252
Elkhart-Goshen, IN	2.10	700	San Jose, CA	0.02	2490
Erie, PA	4.93	653	Santa Barbara-Santa Maria-Lompoc, CA	0.01	2036
Eugene-Springfield, OR	0.31	1064	Santa Cruz, CA	0.00	2295
Fayetteville, NC	2.38	726	Santa Rosa-Petaluma, CA	0.02	1925
Fayetteville-Springdale, AR	3.13	772	Sarasota, FL	0.84	1009
Flint, MI	20.21	442	Savannah, GA	0.44	980
Fort Collins-Loveland, CO	0.35	1071	Scranton-Wilkes-Barre, PA	5.29	745
Fort Lauderdale, FL	1.20	1170	Seattle-Everett, WA	0.33	1621
Fort Myers-Cape Coral, FL	1.50	882	Sharon, PA	4.69	555
Fort Wayne, IN	13.47	614	Sheboygan, WI	0.59	818
Fresno, CA	0.98	1045	Shreveport, LA	6.96	658
Gainesville, FL	0.43	971	South Bend-Mishawaka, IN	3.27	698
Galveston-Texas City, TX	2.02	811	Spokane, WA	1.23	908
Grand Rapids, MI	10.36	723	Springfield, IL	1.50	713
Greeley, CO	1.26	821	Springfield, MO	3.74	722
Green Bay, WI	1.22	841	Springfield-Holyoke-Chicopee, MA	0.40	1154
Greensboro-Winston-Salem, NC	9.86	769	St. Cloud, MN	1.08	802
Greenville-Spartanburg-Anderson SC	9.86	715	St. Louis, MO-IL	12.26	856
Hagerstown, MD	0.22	1008	Stamford, CT	0.00	2850
Hamilton-Middleton, OH	2.31	804	State College, PA	0.22	1007
Harrisburg-Lebanon-Carlisle, PA	2.58	875	Stockton, CA	0.51	1093
Hartford, CT	0.31	1309	Syracuse, NY	8.22	726
Hickory-Morgantown, NC	5.53	658	Tacoma, WA	0.36	1232
Honolulu, HI	0.01	2528	Tampa-St. Petersburg-Clearwater, FL	7.16	916
Houston-Brazoria, TX	30.05	837	Terre Haute, IN	4.02	607
Indianapolis, IN	15.20	771	Toledo, OH/MI	11.89	648
Jackson, MI	2.13	672	Trenton, NJ	0.09	1445
Jackson, MS	5.65	714	Tucson, AZ	2.25	917
Jacksonville, FL	2.52	973	Tulsa, OK	7.09	749
Jacksonville, NC	0.36	854	Tuscaloosa, AL	1.33	763
Janesville-Beloit, WI	1.51	747	Tyler, TX	1.80	751
Johnson City-Kingsport-Bristol, TN/VA	5.52	654	Utica-Rome, NY	6.28	636
Johnstown, PA	14.63	516	Ventura-Oxnard-Simi Valley, CA	0.03	1963
Joplin, MO	7.89	553	Vineland-Milville-Bridgetown, NJ	0.25	972
Kalamazoo-Portage, MI	5.74	701	Visalia-Tulare-Porterville, CA	0.82	908
Kansas City, MO/KS	10.86	827	Waco, TX	2.87	680
Kenosha, WI	0.33	968	Washington, DC/MD/VA	0.67	1689
Kileen-Temple, TX	3.56	706	Waterbury, CT	0.11	1054
Knoxville, TN	4.19	790	Waterloo-Cedar Falls, IA	1.09	743
Lafayette, LA	2.73	747	Wausau, WI	0.80	797
Lafayette-W. Lafayette, IN	1.51	759	West Palm Beach-Boca Raton, FL	0.79	1181
Lakeland-Winterhaven, FL	6.05	696	Wichita Falls, TX	2.89	604
Lancaster, PA	1.30	915	Wichita, KS	9.93	674
Lansing-E. Lansing, MI	3.81	750	Williamsport, PA	1.14	705
Las Vegas, NV	4.53	938	Wilmington, DE/NJ/MD	0.39	1189
Lexington-Fayette, KY	1.08	878	Wilmington, NC	0.22	1127
Lima, OH	2.77	647	Worcester, MA	0.12	1280
Lincoln, NE	2.13	771	Yakima, WA	0.77	849
Little Rock-North Little Rock, AR	6.53	741	York, PA	1.30	920
			Youngstown-Warren, OH/PA	23.87	548