City Size and the Skill Intensity of Production

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September 2006

Abstract: Rauch (1993), Glaeser and Maré (2001), and others have theorized that the productivity of human capital increases with city size. If this is true, one would expect that establishments in large cities use more skill intensive production techniques than those in small cities. In this paper, we use data on the occupational mix at establishments to test whether the skill intensity of production methods varies with city size. Using data from the Occupational Employment Statistics survey, we show that establishments located in metropolitan areas with population below one million use a less skill intensive mix of workers than a comparable group of establishments in metropolitan areas with population above two million. In most industrial sectors, establishments use nearly the same mix of workers in both small and large metropolitan areas. However, we find that the difference in skill intensity is quantitatively important in a few, skill intensive sectors.

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1. Introduction

Labor and urban economists are very interested in understanding why businesses are willing to pay workers in comparable jobs higher wages in large cities than in small cities. Many businesses find the benefits of locating in large cities sufficient to compensate for both higher land costs and higher nominal wages. This implies that many firms that produce goods and services for markets outside of their own city (the traded goods sector) are more productive in a large city than they would be in a small city. If this was not the case, the firms would be likely to relocate to lower cost markets in order to increase profits. They are a number of theories as to why firms are more productive in large cities than in small cities. The theories focus on two types of productivity effects: general productivity effects and human capital productivity effects.

The theories of how general productivity increases with city size tend to focus on gains from concentration.[1] For example, Krugman (1991) theorizes that businesses can reduce transportation costs by locating in cities with many potential customers and suppliers nearby. Large cities may also reduce transportation costs by having transportation links to other cities that are more highly developed than those in smaller cities. In addition, large cities may provide a more comprehensive set of public goods since there are larger pools of firms and people to take advantage of public goods.

The other broad class of theories center on ways in which large cities make human capital more productive. For example, Rauch (1993) argues that cities facilitate knowledge spillovers by putting people in close proximity to other people with valuable knowledge and that businesses that have human capital intensive production functions are more likely to benefit from these spillovers. Workers in large cities may also be higher ability than workers in smaller cities, either because they are attracted by urban amenities or because they selectively migrate to take advantage of higher

[1] This discussion of theories for why businesses are more productive in large cities closely follows the summary in Glaeser and Maré (1994).

wages available to high ability people in large cities (Borjas, Bronars, and Trejo 1992 and Faberman 1998). Glaeser and Maré (1994 and 2001) theorize that cities reduce the cost of acquiring human capital by facilitating interactions with people and therefore skilled workers will be more broadly available in large cities. Wheeler (2001) shows that cities can facilitate the job matching process, so forming worker-firm matches is less costly and more productive in large cities.

In reality, cities' effects on productivity are thought of as some combination of general and human capital productivity effects. For example, agglomeration effects are often thought of as a combination of reduced transportation costs, increased knowledge spillovers, and more efficient industry specific input markets, including labor markets. Theories of this sort explain the tendency of certain industries to be concentrated in one city, such as film production in Los Angeles or commodity trading in Chicago.

There have been a number of papers that shed light on how cities affect productivity by looking at the difference between the wages paid to comparable workers in cities of different sizes and types. Rauch (1993) and Rosenthal and Strange (2005) show that wages increase with the education level of those nearby. Glaeser and Maré (2001), Wheeler (2001), and Kim (2003) provide evidence that the urban wage premium increases with education, suggesting that productivity effects are strongest for highly skilled workers. Similarly, Gould (2005) finds that the urban wage premium is much larger for white collar workers than blue-collar workers. In fact, even though he follows most of the literature and does not condition on the cost of living, Gould finds that the urban wage premium for blue-collar workers can be largely explained by self-selection of high ability blue collar workers to cities. These results suggest that cities do increase the productivity of human capital, but do not rule out an important role for general productivity effects.

While the evidence from the urban wage premium literature is valuable, many of the estimated wage effects are potentially biased due to selective migration and differences across cities in the cost of living. Also, the urban wage premium literature does not give direct evidence about how production techniques differ across cities. It would be interesting to test whether firms' production functions differ by city size, but production functions are difficult to measure.

In this paper, we develop and present a way to measure the skill intensity of firms' production methods using the occupational composition of their workforce. The mix of workers used by a firm provides information about the firm's production process. For example, firms with many workers in high skill occupations have skill intensive production processes. By comparing the occupational mix of establishments in small Metropolitan Statistical Areas (MSAs) to the occupational mix of a comparable group of establishments located in large MSAs, it is possible to test whether production processes differ in skill intensity across MSA size type. It is important to look at a comparable pool of firms because the industrial and establishment size composition of large and small MSAs are different and these factors affect occupational mix. We find evidence that firms in small MSAs are less skill intensive than similar firms in large MSAs.

Many of the theories regarding how cities affect human capital productivity suggest that the productivity effects would be strongest in skill-intensive industries. For example, Rauch (1993) theorized that knowledge spillovers are more likely to be capitalized by firms with knowledgeable workers than by other firms. Studying how skill intensity varies across city type by industrial sector can shed light on whether the differences are concentrated in certain sectors of the economy. Consistent with Rauch's hypothesis, we find that skill intensive sectors are more skill intensive in large cities. The differences in occupational mix across MSA size type in less skill intensive sectors are minor; some sectors appear to be less skill intensive in large MSAs than in small MSAs.

The paper is organized as follows. The next section presents a theoretical model which shows the relationship between the skill intensity of production and differences in human capital productivity across city size types. Section 3 discusses the Occupational Employment Statistics survey microdata we use in the analysis. Section 4 describes the methodology used and the results are presented in section 5. The paper ends with conclusions.

2. Theory of human capital productivity and skill composition

The following representative firm model of labor demand illustrates the link between human capital productivity and occupational mix. The model assumes that there are two types of workers, high skill and low skill, denoted by *H* and *L*. It is assumed that there is a fixed amount of capital required per worker of each type regardless of city size type, k^s for $s=\{H, L\}$. The cost per worker of type *s*, w_j^s, reflects this and $w_j^s = \omega_j^s + r_j k^s$, where *j* indexes city. Assume that there are two cities indexed with *j*=0,1. For simplicity, all firms produce the same good that sells for p_j in city *j* and there is no trade between the cities.

A firm in city *j* solves the following profit maximization problem:

$$\max_{H,L} \pi_j = p_j \varphi_j (\theta_j f(H) + g(L)) - (w_j^H H + w_j^L L) \qquad (1)$$

where φ_j is the general productivity multiplier in city *j* and θ_j is the productivity multiplier specific to high skill workers in city *j*. The worker type specific production functions $f(H)$ and $g(L)$ do not vary across city type. Both $f(H)$ and $g(L)$ have positive first derivatives and negative second derivatives. We assume that $\frac{\partial f(n)}{\partial n} > \frac{\partial g(n)}{\partial n}$ and $\frac{\partial^2 f(n)}{\partial n^2} > \frac{\partial^2 g(n)}{\partial n^2}$, meaning that the marginal product of high skill workers is greater than the marginal product of low skill workers and the marginal product of high skill workers diminishes at a slower rate than those of low skill workers. Rearranging the first order conditions from (1) shows that:

$$\theta_j \frac{f'(H_j)}{g'(L_j)} = \frac{w_j^H}{w_j^L} \qquad (2)$$

where $\{H_j, L_j\}$ is the profit maximizing mixture of high and low skill workers in city *j*. This shows that the firm chooses the mixture of workers such that the marginal benefit from hiring a high skilled worker relative to that from hiring a low skill worker is the same as the relative costs for the two types of workers. Note that neither the price of the output nor the general productivity multiplier enter into equation (2). Define the following ratios:

$\Phi_j = {f'(H_j)}/{g'(L_j)}$ and $\Omega_j = {w_j^H}/{w_j^L}$. Comparing the maximizing worker mixes of firms in cities 1 and 0 shows that:

$$\frac{\Phi_0}{\Phi_1} = \frac{\theta_1/\theta_0}{\Omega_1/\Omega_0}. \tag{3}$$

Given the assumptions stated above about $f(.)$ and $g(.)$, (3) implies that if

$\theta_1/\theta_0 > \Omega_1/\Omega_0$ then $H_1/L_1 > H_0/L_0$ (this also holds if > is replaced with = or <).

In other words, the model suggests that the firm in city 1 uses a more skill intensive mix of workers than the firm in city 0 if the ratio of the productivity multipliers of high skill workers in cities 1 and 0 is higher than the ratio of the relative cost of high skill workers in cities 1 and 0. This result is intuitive: if an input is more heavily used by firms in city 1 than by comparable firms in city 0, then the input is either: relatively less expensive in city 1 than city 0, more productive in city 1 than in city 0, or both. This suggests that differences in skill mix in similar firms across city types can provide evidence as to whether cities increase the productivity of human capital, especially when combined with information on how costs per worker vary by skill type and city type.

The urban wage premium literature provides estimates on how wages vary with city type and skill. These estimates can be transformed to provide estimates of relative wages across skill type and city type. However, the relative wage figures do not include any information on how capital costs per worker varies across worker or city type. If we assume that capital per worker is ignorable, the estimates of Ω_1/Ω_0 from the urban wage premium literature range from 1.03 to 1.10, meaning that the relative wage of high skill workers is higher in large cities than in small cities.[2] The capital cost per worker almost certainly varies with city type, primarily due to differences in the cost of land. Given the concentration of high skill workers in expensive locations (e.g. downtown) and the concentration of low skill workers in less expensive areas (e.g. industrial parks), it seems likely that high skill workers and expensive land are complements in production. This would reinforce the pattern in wages and suggests that, even including capital costs per worker, Ω_1/Ω_0 would be greater than one. If one takes as given that Ω_1/Ω_0 is at least one, then if firms in small cities are less skill intensive than those in large cities it is strong evidence that human capital is more productive in large cities. The rest of this paper is devoted to testing whether firms in small cities use a more or less skill intensive mix of workers than those in large cities.

3. Occupational Employment Statistics survey micro-data

The data used in this paper are the micro-data from the Bureau of Labor Statistics' (BLS) Occupational Employment Statistics (OES) surveys from 2001 through 2003. The OES survey measures occupational employment and wage rates for wage and salary workers in non-farm establishments in the 50 states and the District of Columbia. The OES survey covers all industries except for portions of the Agriculture sector and Private Households. The data is used to create the annual publication *Occupational Employment and Wages*. The following description summarizes the

[2] The 1.03 figure is derived from Table 1 of Wheeler (2001), using population of 5 million as the large city population, population of 500,000 as the small city population, people with 16+ years of school as high skill, and people with 9-12 years of school as low skill. The figure of 1.10 is derived from Table 4 in Glaeser and Maré (2001) and large cities are defined as metropolitan areas with a central city with population above 1 million, small cities are all other areas, high skill workers are those with 16 years of education, and low skill workers are those with 12 years of education.

information on survey methodology provided in *Occupational Employment and Wages, May 2003* (Bureau of Labor Statistics 2004).

Through mail-in surveys and telephone contact, responding establishments report the number of employees by occupation using the Standard Occupational Classification (SOC) system. The SOC system includes 801 detailed occupations. Covered employees include all full- and part-time wage and salary employees, including those who are temporarily absent. Excluded from employment are contract workers, self-employed owners, partners in unincorporated firms, household workers, and unpaid family workers. For each occupation, establishments report the number of employees in each of 12 wage intervals. To create mean wage and other occupational wage statistics, the wage interval data is combined with data from other sources to generate information on wage distributions and changes in wages over time.[3]

The OES survey uses a survey design consisting of six probability sample panels of approximately 200,000 establishments that are selected bi-annually. The samples are constructed such that the six panels combined form a sample of establishments that is representative of the universe of establishments by substate area, industry, and establishment size class. The substate area definitions used in the survey are metropolitan statistical areas, consolidated metropolitan statistical areas, and non-metropolitan balance of state areas.[4] A full set of six panels provides a sample of approximately 1.2 million establishments, which means that 18 percent of in-scope establishments are surveyed once in a set of panels.[5] The use of biannual panels began in 2002 and the data used in this study is drawn from an annual panel in 2001, two biannual panels in 2002, and two biannual panels in 2003.

[3] BLS's Employment Cost Index survey for nine major occupational groups is used to adjust for collecting the data at different times. BLS's National Compensation Survey is used to generate mean wage for each {occupation, wage interval} cell in order to estimate mean wages.

[4] Depending on the state, there are one to six balance of state areas per state.

[5] Approximately 2 percent of the establishments in a set of six panels are certainty units, meaning that they are sampled once in every six panel set.

In the May 2003 survey, about 79 percent of establishments in the sample responded to the survey and these respondents represent 72 percent of pre-survey weighted employment (BLS 2004). For nonresponding establishments, occupational employment patterns are imputed using a hot-deck procedure where nonrespondents are given the occupational mix of the responding establishment that has the most similar combination of industry, employment size, and geographic area. Wage distributions are imputed using the empirical distribution of all responding establishments in the same geographic area, industry, and size class cell as the nonrespondent. In both of the imputation stages, if an insufficient number of responding establishments is found, the restrictions on area, industry, and size are loosened until imputation is possible.

One can think of the OES micro-data as linked employer-employee data where the only thing known about each employee is their occupation, their wage interval, and the industry, location, and size of the establishment where they work. While the information on each worker is limited, this information is known for all workers at the same establishment at the same time. Unlike most other sources of linked employer-employee data for the United States, the OES micro-data is reported by establishment rather than constructed through record linkage. It covers all regular employees at an establishment, rather than those in a subset of occupations or only those who can be linked to the establishment through record linkage. This makes the OES micro-data well suited to study how the occupational mix of comparable groups of establishments differs across city size types.

The published OES data has been used by other authors to look at differences in occupational composition and wages across states and metropolitan areas. For example, Hajiha and Salmon (2005) provide maps that show how employment concentrations vary among states and metropolitan areas by major occupational group. In similar work, Cover (2005) compares the occupational distribution of metropolitan and non-metropolitan areas and shows that occupations' wages tend to be higher in whichever area type they are concentrated in. Watson (2005) finds that the occupational mix is different in fast, moderate, and slow growing metropolitan areas. Kilcoyne (2004) uses shift share analysis to show that the differences in mean wages across states is primarily explained by within occupation differences in wages, but that the occupation mix also plays a role. None of these studies control for differences in industrial composition or establishment size across different geographic areas.

4. Methodology

There are several components to using the OES micro-data to study how skill intensity varies across city types. Establishments have to be classified based on city size type. To facilitate summarizing and comparing skill distributions, it is helpful to create a continuous variable that describes the skill level of each occupation. This skill measure has to be combined with information on occupational mix to provide a measure of skill intensity for a group of establishments. Then it is necessary to construct comparable sample of establishments from large and small cities. Finally, the skill mix of comparable firms from both city types has to be compared. Each of these components of the methodology is discussed in turn.

There is no established definition of what constitutes a small, large, or medium city. In our analysis, MSAs are treated as equivalent to cities and the definitions used are as follows. The categories are defined using 2000 population for MSAs as follows: small MSAs have population of no more than one million, medium MSAs have population between one and two million, and large MSAs have population of at least two million.[6] The large MSAs include the 22 largest MSAs, the medium MSAs include the next 28 largest MSAs, and the remaining 228 MSAs are small MSAs.[7] The definitions used were chosen based on looking at kink points in the distribution of population

[6] MSAs are defined as either Consolidated MSA or MSAs, using the definitions of Consildated MSAs and MSAs that was used in collecting the 2000 Census.

[7] MSAs in Puerto Rico are excluded from the sample.

size across MSAs and the desire to use round numbers. Table 1 shows the largest and smallest MSAs for each category.

To facilitate summarizing skill intensity across industries and MSA types, it is helpful to have a continuous measure of how skilled each occupation is. The challenge in constructing a broadly applicable skill index is that different occupations require very different sets of skills. While it is easy to compare skill level between similar occupations (e.g. chef versus short order cook), it is difficult to do so for dissimilar occupations (e.g. chef versus auto mechanic). Creating an index of educational and training requirements is one approach, but it would miss hard to measure skills such as sales talent or creativity. To deal with these challenges, the measure of occupational skill we use is the mean wage paid to workers in an occupation by firms in the middle size category of cities. The premise is intuitive: occupations that are more highly paid are more skilled occupations.

Mean wage in the medium MSAs is used to avoid biasing the skill intensity comparisons. Nominal wages are undeniably higher in large MSAs than in small MSAs. Using the national average wage of wages would cause the skill measure to be biased by the share of an occupation in each MSA size class. More precisely, the national average wage would be $\bar{w}_j = \rho_{jS}\bar{w}_{jS} + \rho_{jM}\bar{w}_{jM} + \rho_{jL}\bar{w}_{jL}$, where $\bar{w}_j$ is the national mean wage, $\bar{w}_{jq}$ is the mean wage for occupation *j* in size class *q* (which is *S*, *M*, and *L* for small, medium, and large MSAs respectively), and ρ_{jq} is the proportion of employment in occupation *j* in MSA size class *q*. If $\rho_{jL} \neq \rho_{jS}$ and $\bar{w}_{jL} \neq \bar{w}_{jS}$, then $\bar{w}_j$ would be affected by what we want to measure, the distribution of occupations across MSA types. Another benefit of using $\bar{w}_{jM}$ is that the medium sized cities are the most homogenous of the three MSA types. The largest medium MSA is the Cincinnati--Hamilton, OH--KY--IN CMSA (population of 1.98 million) and the smallest is the Louisville, KY--IN MSA (population of 1.026 million). For these reasons, the measure of the skill of occupation *j* is the mean hourly wage for occupation *j* in medium sized MSAs, which we call the medium wage for occupation *j*. The medium wages are calculated using an adaptation of the computer programs used to create the published data in the 2003 Occupational Employment and Wages published data, so the method is similar to that described in the OES documentation (Bureau of Labor Statistics 2004). The only modification is that mean wages are estimated by MSA type rather than another geographic unit.

The next component of the methodology is using the medium wages and the occupational mix of firms to compare the skill intensity of their production processes. To show how occupational mix provides information about production processes, consider the following example. Suppose there are two screw manufacturers, Joe's Bolts and Precision Bolts, with the mix of workers described in Table 2. Joe's and Precision use the same mix of workers except that Joe's employs seven non-computer controlled machine operators and a machinist while Precision employs seven computer-controlled machine operators and a computer-controlled machine programmer. Based on the job duties of each of these occupations, we can infer that Joe's uses less sophisticated, and probably older, machinery than Precision.

To come to this conclusion, not only did we need to know that Joe's and Precision are in the same industry, but we had to know something about the production technology choices available to them. It would require equivalent knowledge of all industries to make similar inferences for the economy as a whole. Lacking that knowledge, we limit the focus to comparing skill intensity, rather than production processes as a whole. To quantify skill intensity, we first calculate the percent of employment at each establishment in each occupation and find the percentage point difference in occupational employment across the two establishments (see the fourth column of Table 2). Then we relate the percentage point difference in occupational employment to the medium wage. For this example, we use an occupation-level regression where the dependent variable is the percentage point difference in occupational employment and the independent variable is the natural log of medium wage. This produces the slope coefficient -0.0015 and, since this is negative, we conclude that Joe's production method is less skill intensive than Precision's.

For the estimates in the paper, we do not compare single establishments but instead compare similar groups of establishments. Small establishments have lumpy occupational distributions and comparing groups of establishments smoothes over this lumpiness. The other difference between the actual methodology and the example is that most of the results are presented graphically. There are interesting patterns in the distribution of employment at different points of the skill distribution that lend themselves to graphical presentation rather than regressions.

To create comparable groups of establishments, we form samples of establishments that are comparable to one another from large and small cities. MSA size type, indexed with *q*, is S for small MSAs and L for large MSAs. Q_{lq} is an indicator variable that equals one if establishment *l* is located in MSA size type *q* and zero otherwise. D_{liz} equals one if establishment *l* is in industry *i* and employment size class *z* and equals zero otherwise. M_{iz} equals one if there is positive employment in industry *i* and employment size class *z* in both MSA size types; otherwise M_{iz} equals 0.

Employment in occupation *j* in establishment *l* is e_{jl} and is weighted using the survey weights to make the sample of establishments match the universe of establishments. Define the total employment in industry *i*, employment size class *z*, and MSA size type *q* as $E_{iz,q} = \sum_j \sum_l Q_{lq} D_{liz} e_{jl}$.

Total employment in MSA size type *q* is $N_q = \sum_i \sum_z M_{iz} E_{iz,q}$. Note that N_q excludes employment for industry and employment size class pairs that have zero employment in either MSA size type.

In order to generate comparable sets of establishments across MSA size types, establishments are weighted such that the industry and employment size class distribution of employment is the same for both sets of establishments. The MSA size type that the data is adjusted to match is indexed with r =S,L. The weight used to make the employment distribution of MSA size type q comparable to that of MSA size type r is:

$$\omega_{iz,q|r} = \frac{(E_{iz,r} / N_r)}{(E_{iz,q} / N_q)}.$$

The count of employment in occupation j in MSA size type q and weighted to be comparable to MSA size type r is $e_{j,q|r} = \sum_i \sum_z \omega_{iz,q|r} M_{iz} \sum_l Q_{lq} D_{liz} e_{jl}$. When weighting such that the industry and employment size class distribution of employment in MSA size type q is comparable to that of MSA size type r, the percent of MSA size type q employment that is in occupation j is:

$$p_{j,q|r} = 100 \frac{e_{j,q|r}}{\sum_j e_{j,q|r}}.$$

We simplify the notation for cases where q=r such that $p_{j,q|r} = p_{j,q}$. For brevity, we use j's occupation share interchangeably with the percent of employment in occupation j. The method used to generate the occupation shares for a single industrial sector is the same as above, except that the sample is first restricted to only establishments in the sector of interest.

The industry codes used for the analysis are the same as are used in OES publications, which are a combination of four and five-digit NAICS2002 codes. The establishment size classes used are also the same as in OES publications. The establishment size class ranges are: (1) 1-9, (2) 10-19, (3) 20-49, (4) 50-99, (5) 100-249, and (6) 250+. The program used to generate the employment counts by industry, establishment size class, and MSA size type cells is adapted from the program used to create the *Occupational Employment and Wages, May 2003*. It is adapted to exclude the Agricultural sector and a single occupation that has no employment in medium MSAs.[8] The program is also altered to produce counts for each MSA size type rather then more typical geographic units.

To test whether establishments use different production processes in small MSAs than in large MSAs, it is necessary to use comparable sets of establishments. Using the methodology discussed in that last paragraph, this can be done either by weighting establishments in large MSAs to be comparable to those in small MSAs or vice versa. The economies of large MSAs tend to be more diverse than those in small MSAs, both in terms of industry composition and employment size composition. This means that weighting establishments in large MSAs to be comparable to establishments in small MSAs requires fewer large weights than vice versa. There are 2,035 industry, employment size class pairs with positive employment in the OES sample used for this paper. Of those, 30 have zero employment only in small MSAs and five have zero employment only in large MSAs. This implies that weighting large MSA establishments to be comparable to small MSA establishments generates the most comparable set of establishments possible. Therefore, we weight large MSA establishments to be comparable to small MSA establishments and use $p_{j,S}$ and $p_{j,L|S}$.

The next piece of the methodology is relating the occupation shares to skills through graphs and regressions. The graphs use a local weighted smoothing estimator to show how the difference between MSA size types in the share of employment in occupation *j* varies with skill, as measured by medium wage. Specifically, the graphs relate $\Delta_{j,L\,|\,S} = p_{j,S} - p_{j,L\,|\,S}$ to the natural log of $\overline{w}_{jM}$ using a locally weighted smoothing estimator with tri-cube weighting and a bandwidth of 0.2.[9] The confidence intervals on the graphs are derived from boot-strapped standard errors, where the

[8] There is one occupation that has employment in both large and small cities but not in medium cities. Since it is impossible to calculate the medium wage for this occupation, it is dropped from the analysis and does not contribute to the figures. According to Table 1 of *Occupational Employment and Wages, May 2003*, there were less than 725 workers in the occupation in the United States.

[9] See the description of the "lowess" command in StataCorp (2005) for more details on the locally weighted smoothing estimator.

bootstrapping is done over establishments with 200 replications.[10] One graph relates percentage difference between MSA size types in *j*'s occupation share, $per\Delta_{j,L\mid S} = \ln(p_{j,S} / p_{j,L\mid S})$. In addition, the following regression is estimated with ordinary least squares:

$$p_{j,S} = \alpha + \gamma p_{j,L\mid S} + \beta \ln(\overline{w}_{j,M}) + \varepsilon_j .$$

The regressions are estimated for the economy as a whole and separately for each industrial sector.

This methodology is well suited to the data and question at hand, but it has some limitations. The measured differences in occupational mix across MSA size types may reflect differences in the productivity of people in the occupations across MSA size type, rather than differences in human capital productivity. It could be that large MSAs attract highly productive workers who would be equally productive in all MSAs. Firms in large MSAs may react to the availability of these highly productive workers by hiring more workers in the occupations in which they are concentrated. If the ability differences are particularly strong for high skill workers, this could lead to the same pattern regarding skill utilization that would come from large MSAs having higher human capital productivity than small MSAs.

While there is evidence that high ability workers are more likely to migrate (Borjas, Bronars, and Trejo 1992) and are drawn to large MSAs (Faberman 1998), it is not clear that they are drawn for reasons other than increasing expected lifetime income. If, as found by Borjas, Bronars, and Trejo (1992), high ability workers migrate because they are able to receive higher real wages, then ability differences are largely a by-product of the productivity differences that lead to the urban wage premium. The most common alternate explanation of why high ability workers would selectively migrate to large MSAs is that they are attracted to urban amenities, such as shopping and entertainment variety. Given that high ability workers also tend to have higher income, the urban

[10] The bootstrapping follows the sample design. Random samples of establishments are chosen within each survey strata and the number of establishments sampled per strata is constant across replications. The strata for the OES survey are year, state, sub-state geography, 4 or 5-digit NAICS code, and establishment size class.

amenity argument is called into question by the following anecdotal evidence: many high income workers live in the less urban portions of MSAs, high ability urban residents often spend leisure and vacation time in non-urban areas, and many high ability urban residents leave large MSAs when they retire. The fact that the urban wage premium remains large even when conditioning on hard to observe measures of ability (Glaeser and Maré 2001 and Gould 2005) also suggests that ability differences only partially explain differences in labor markets in large and small MSAs. Therefore, it is unlikely that difference in ability fully explains differences in skill intensity.

The analysis depends on comparing groups of establishments that produce a similar set of goods and services. If there is heterogeneity in what establishments produce within an industry and establishment size class cell, then controlling for industry and size class composition may be insufficient to form comparable sets of establishments. In the OES survey, most industries are measured at the 4-digit NAICS level of detail, with a few industries measured at the 5-digit level of detail. This means that, for example, the industry group Other Nondepository Credit Intermediation (52229-) includes the following industries: Consumer Lending, Real Estate Credit, International Trade Financing, Secondary Market Financing, and All Other Nondepository Credit Intermediation. If these industries are heterogeneous in their occupational mix and MSA size type, it could lead to concluding that skill mix varies with MSA size type even if it does not. The OES survey makes an effort to use 5-digit NAICS codes where there are major differences within 4-digit NAICS codes. As an example, movie theaters are given a different industry code from all other portions of the Motion Picture and Video Industries group, which primarily consists of motion picture and video production and distribution industries.

There are a few other limitations worth mentioning. The OES survey treats part-time and full-time workers as equivalent. If establishments in small and large MSAs differ in their utilization of part-time workers, this would make their occupational distribution of employees different even if the occupational distribution of hours worked is the same. Establishments with allocated data are kept in the sample when creating $p_{j,S}$ and $p_{j,L\,|\,S}$. By keeping them in the sample, the industry and establishment size distributions are made more representative than they would be without the establishments with allocated data. While imputations are done within substate area when possible, it is possible that data from establishments in small MSAs are used to impute for establishments in large MSAs (or vice versa). Finally, this method can only pick up indirect effects of differences in the utilization of more or less skilled workers within an occupation. As an example, because there is only one lawyer occupation, a low-fee general attorney contributes as much to the skill measure as a highly specialized merger and acquisitions attorney even though the later is probably more skilled. Most likely, this limitation biases the estimates of differences in skill intensity toward finding no difference.

5. Results

Prior to looking at the results that use detailed occupation, it is informative to look at the occupation distributions in different MSA size types at the major occupational group level of aggregation. Figure 1 shows the percent of employment in each of the major occupational groups for small and large MSAs, as well as for large MSAs adjusted to have the same industry and establishment size distribution as the small MSAs. For the remainder of the paper, the true figures for the large MSA sample will be called unconditional and figures from the large MSA sample that has been weighted to be comparable to the small MSA sample will be called conditional. The occupation groups in Figure 1 are sorted so that those with the highest wages in medium MSAs are at the top of the graph and those with the lowest are at the bottom.

The most noticeable fact about Figure 1 is that the occupational distributions are fairly similar across MSA size types. This is especially true when comparing the occupational distribution of small MSA sample to the conditional large MSA sample, indicating that industry and establishment size distribution has an effect on occupational mix. Looking at these comparable groups of establishments, the greatest percent difference between them is in Legal occupations, where employment is 14 percent lower in the small MSA sample than in the conditional large MSA sample.[11] The next largest difference is in the Computer and Mathematical occupation group (11 percent lower in small MSAs). Ignoring differences across MSA types in industry and establishment size distributions would make the differences in occupational distribution starker. For example, the percent difference between unconditional large MSA and small MSA samples are 44 percent and 61 percent for Legal and Computer and Mathematical occupation groups respectively.

Taken as a whole, Figure 1 shows that establishments in small MSAs use a less skilled mix of employees. For high wage occupations, the percent of employment in an occupation group is generally higher in the conditional large MSA sample than in the small MSA sample. The chief exception is Healthcare Practitioners and Technical occupations, where employment is three percent higher in small MSAs. All five of the lowest wage occupation groups are more prevalent in the small MSA sample than in the conditional large MSA sample.

Studying occupation groups rather than specific occupations can mask differences in skill intensity because of heterogeneity in skill level within occupational group. The rest of the analysis uses detailed occupational employment to look at differences in occupational mix across MSA size types. Table 3 provides medium wages, $p_{j,S}$, $p_{j,L}$, and $p_{j,L\,|\,S}$ for a few occupations. This table shows that the occupational categories are quite detailed. For example, Credit Analysts and Management Analysts are separate occupations. The table is sorted by medium wage and the

[11] Throughout the paper, percentage point differences are calculated as ln(X/Y). This method has the advantage that the percent differences are not affected by which group is used as the comparison group. The percent difference between X and Y is the negative of the percent difference in Y and X.

ordering of occupations is consistent with prior expectations about which occupations are most skilled. For example, Auto Mechanics and Machinists have the same medium wage.

Figure 2 is a smoothed graph of the percentage point difference between small and large MSAs in occupational employment. Each point on the line represents a single detailed occupation. For clarity and confidentiality, occupations are indicated not by their occupation code but by their mean wage in the medium MSAs. A positive (negative) difference indicates that occupations with that range of medium wage have a larger (smaller) share of employment in the small MSA sample. Note that very different occupations can be adjacent to one another since the order in which occupations are shown is determined entirely by wage. The medium wage axis has a log scale.

The solid line on Figure 2 shows the difference in occupational mix between the small MSA sample and the conditional large MSA sample. Establishments in small MSAs do use a less skill intensive mix of employees than comparable establishments in large MSAs. Essentially, occupations with a medium hourly wage below $20 have a slightly higher share of employment in small MSAs, although the smoothed difference is always less than a 0.01 percentage point difference. Occupations with a medium hourly wage above $20 have a noticeably smaller share of small MSA employment, with a difference that ranges as large as approximately -0.02 percentage points. For most occupations, the difference across MSA types is statistically significant, as indicated by the shaded confidence intervals. As a reminder, the wages are only used to describe skill level and are not calculated with data from either large or small MSAs. Consequently, this graph is not affected by the urban wage premium. The dashed line shows the differences in skill mix between the small MSA sample and the unconditional large MSA sample. Given the large differences in industry and establishment size composition, it is not surprising that establishments in the unconditional large MSA sample use a much more skill intensive mix of workers than do those in the small MSA sample.

Figure 3 is the counterpart of Figure 2, but using percent difference rather than percentage point differences. The percent difference graph puts relatively more visual weight on occupations in the tails, which represent a small fraction of employment. The benefit of Figure 3 is that is easy to interpret. It shows that employment in occupations with medium wage of $40 is approximately 10 percent lower in the small MSA sample than in the conditional large MSA sample. Overall, the percent differences in occupational employment confirm what was shown with the percentage point differences: establishments in small MSAs use a less skill intensive mix of employees than comparable establishments in large MSAs.

The question remains as to whether these differences are large or small. To address this subjective question, it is helpful to compare the results to a case where we have a sense of the difference in skill level. To do this, we repeat the analysis comparing the occupational distribution of non-durable manufacturing (NAICS code beginning with 31 or 32) to that of durable manufacturing (NAICS code beginning with 33). Non-durable manufacturing includes producers of clothes, food products, chemicals, etc. Durable manufacturing includes producers of cars, machinery, computers, and other similar items. One would expect non-durable manufacturing to be less skill intensive than durable manufacturing and that the difference in skill intensity would be smaller than that between less similar sectors (e.g. Retail Trade and Manufacturing). By comparing two classes of manufacturing establishments, there is a larger degree of overlap in the occupations across the two subsectors than there would be in comparing less similar sectors. To keep the comparison straightforward, only manufacturing establishments located in large MSAs are used to get the occupational distribution in these subsectors.

Figure 4 shows the difference in occupational mix between non-durable and durable manufacturing establishments and repeats the graph from Figure 2 that compares small MSA establishments to comparable large MSA establishments. As expected, the non-durable manufacturers use a less skilled mix of employees than durable manufacturers. This is reassuring evidence that the skill intensity measures we use effectively capture differences in skill intensity. The difference in occupational mix between the two classes of manufacturing establishments is much greater than that between the MSA size types. While the maximum difference across MSA size types is approximately 0.02 percentage points, the greatest difference across manufacturing subsectors is approximately 0.2 percentage points. This leads to the conclusion that the differences in skill intensity between comparable establishments in small and large MSAs are mild relative to the differences across these two subsectors.

While the graphs allow one to see patterns in employment throughout the skill distribution, it is hard to compare differences across a number of sectors. To test whether in general establishments in small MSAs use a less skill intensive mix of workers than comparable establishments in large MSA, we estimate the model $p_{j,S} = \alpha + \gamma p_{j,L \mid S} + \beta \ln(\overline{w}_{j,M}) + \varepsilon_j$, where an observation is at the occupation level. If $\hat{\beta}$ is positive (negative), it tells us that establishments in small MSAs use a more (less) skill intensive workers than those in large MSAs, since conditional on the percent of large MSA employment in an occupation the percent of small MSA employment increases (decreases) with the log of the occupation's mean wage in medium MSAs.

The regression results for all sectors pooled together are on the top row of Table 4. $\hat{\beta}$ is -0.01 and highly statistically significant, confirming that establishments in small MSAs are on average less skill intensive than comparable establishments in large MSAs and that the difference in skill intensity is statistically significant. The bottom row of Table 4 has the results from a similar regression comparing the skill intensity of Non-durable Manufacturing and Durable Manufacturing. The coefficient from this regression is -0.155. As in the graphs, the difference in skill intensity across MSA size types is small relative to the difference between the two manufacturing subsectors.

Many of the theories of why human capital would be more productive in large MSAs suggest that the productivity gains should be strongest for establishments that use skill intensive production processes. According to these theories, human capital intensive industries would have larger differences in skill mix than other industries. To see if this is true, we repeat the process of creating occupational mix data by sector and estimate regressions separately for each sector. The results of these regressions are also in Table 4.

We find that the differences between the skill mix of establishments in small and large metropolitan areas are more pronounced for a few sectors. The sector with the largest difference in skill mix is the Information sector, which includes television, radio, and movie producers and publishers. The difference in the information sector (-0.076) is approximately seven times as large as the difference for the economy as a whole. The other sectors where the differences in skill intensity across MSA size types are significantly different from those for the economy as a whole are (in descending order of coefficient on log wage): Utilities; Professional, Scientific, and Technical Services; Management of Companies and Enterprises; Finance and Insurance; and Wholesale Trade. These sectors have slope coefficients ranging from -0.053 to -0.031. While the slope coefficient for Mining is more than twice as negative as that for the economy as a whole, the coefficient is not significantly different from zero or the coefficient for the economy as a whole.

Sectors where the differences in skill intensity across MSA size types are similar to those found for the economy as a whole are: Arts, Entertainment, and Recreation; Manufacturing; Real Estate; Construction; Health Care and Social Assistance; Administrative and Support et al; and Educational Services. These sectors have coefficients on log wage ranging from -0.021 to -0.011 and only the coefficients for the Manufacturing and Administrative sectors are different from zero at the five-percent level of significance. The point estimates for Retail Trade and Other Services are effectively zero, showing that the skill intensity of establishments in these industries does not vary with MSA size. In the remaining two sectors, Transportation and Warehousing and Accommodation and Food Services, the point estimates are 0.021 and 0.022, respectively. These estimates suggest that establishments from these sectors in small MSAs are more skill intensive than comparable establishments in large MSAs. However, the coefficients are not statistically significant for these sectors.

Figure 5 has graphs that show how the skill mix varies across MSA size for four sectors: (a) Information; (b) Professional, Scientific, and Technical Services; (c) Retail Trade; and (d) Health Care and Social Assistance. These graphs follow the same structure as Figure 2: the difference in occupations' shares of employment in each MSA size type is related to the occupations' mean wage in medium MSAs. The Information (Fig. 5a) and Professional, Scientific, and Technical Services (Fig. 5b) sectors both have large differences in skill intensity across MSA size types. Relative to comparable establishment in large MSAs, establishments in these sectors in small MSAs use a larger proportion of employees in low to middle skill occupations and a much smaller proportion of employees in high skill occupations. While the regression results indicate that there is no difference in skill intensity in the Retail Trade sector, Figure 5c shows that Retail Trade establishments in small MSAs use more low skill workers and fewer of the lowest skill workers than their counterparts in large MSAs. In the Health Care and Social Assistance sector, establishments in small MSAs use less highly skilled workers and more low skilled workers than those in large MSAs, but the differences are small.

6. Conclusions

Using data from a large, representative survey of establishments, we find that establishments in small MSAs use a less skilled mix of employees than do comparable groups of establishments in large MSAs. The differences in skill intensity across MSA size type are of a small magnitude, even in the sectors where the differences are statistically significant. The difference in skill intensity between non-durable and durable manufacturing is twice the magnitude of the difference between establishments in small and large MSAs in the sector with the greatest difference in skill intensity (Information). In most sectors, the differences in skill intensity across MSA size types are small. The sectors where there are not any significant differences in skill intensity employ over 60 percent of private-sector workers.

Overall, the results support the theory that human capital is more productive in large MSAs than in small MSAs. In nearly all industrial sectors, establishments in small MSAs use a less skill intensive mix of workers than do establishments in large MSAs. If the cost of high skill workers relative to the cost of low skill workers in small MSAs is less than or equal to that in large MSAs, the differences in occupation mix imply that human capital is more productive in large MSAs than in small MSAs. In the most skill intensive sectors, the differences are significant both quantitatively and statistically. This is consistent with the theory that industries that use highly skilled workers are the ones most affected by human capital productivity increases.

It is not surprising that sectors with large differences in skill intensity across MSA size types are also the ones that are strongly concentrated in large MSAs. Since large MSAs enhance the productivity of establishments in these sectors more than other sectors, we would expect them to be concentrated in large MSAs. The methodology used here can not distinguish between the various reasons that sectors that are less skill intensive in small MSAs than large MSAs are also more highly concentrated in large MSAs. It could be that these sectors are more skill intensive in large MSAs due to concentration, which provides thicker labor markets and more workers with the required skills. It could also be that these sectors are concentrated in large MSAs because large MSAs make them more productive, regardless of concentration. Finally, these patterns may be due to differences across MSA size types in the goods and services produced by establishments in the same industry and establishment size class.

An interesting extension of the work in this paper would be to look at how differences in skill intensity by MSA size type vary across traded and non-traded sectors. It is likely that differences in productivity across MSA size type are most prevalent in the traded sector. This is because costs are higher in large MSAs than small MSAs and prices are set by the national or international market in the traded sector. Without productivity gains from locating in large MSAs, establishments in the traded sector would locate in small, lower cost MSAs.

The final conclusion is that there is great potential for other research using the OES micro-data. The occupational employment data in the OES data provides a way to measure production processes at the establishment level, which is unusual outside of the manufacturing sector. This information can enable one to look at a number of research questions, such as quantifying the degree of heterogeneity in production processes, looking at how firm survival and expansion probabilities are related to skill intensity, and studying how the mix of occupations at establishments adjust to the skill mix of the population. The Bureau of Labor Statistics has a system that allows outside researchers access to micro-data files; more information on that program is available at http://www.bls.gov/bls/blsresda.htm.

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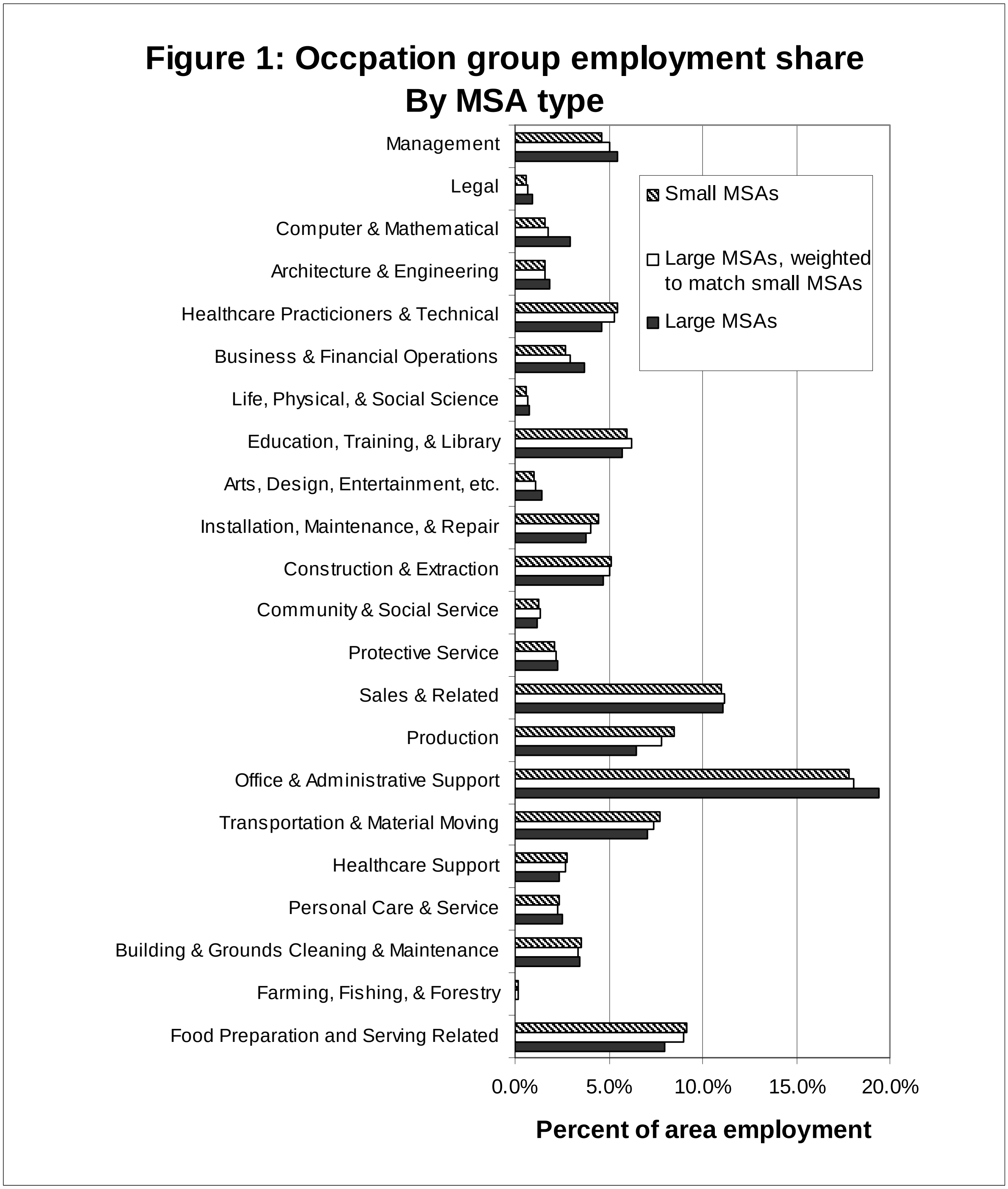


Source: Authors calculations from OES micro-data

Notes: Large MSAs are MSAs and CMSAs with population over 2 million in April 2000. Small MSAs are MSAs and CMSAs with population below 1 million in April 2000. The "Large MSAs, weighted to match small MSAs" is the sample of establishments of establishments in large MSAs weighted to have the same industry and establishment size composition as is in small MSAs. See paper for details.

Figure 2: Comparison of occupational mix in small and large MSAs

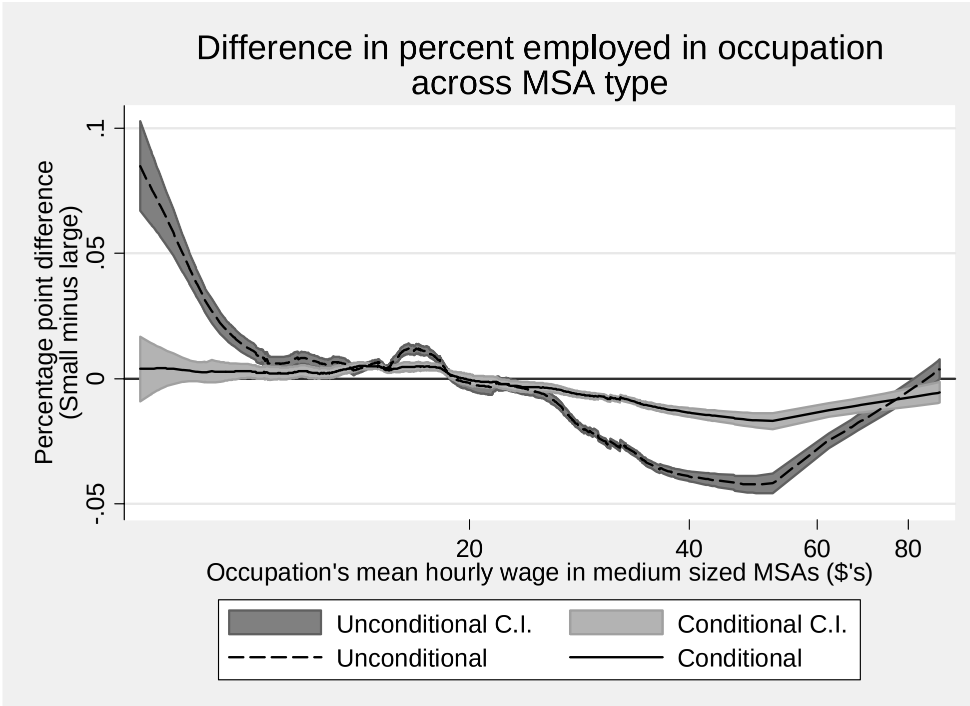
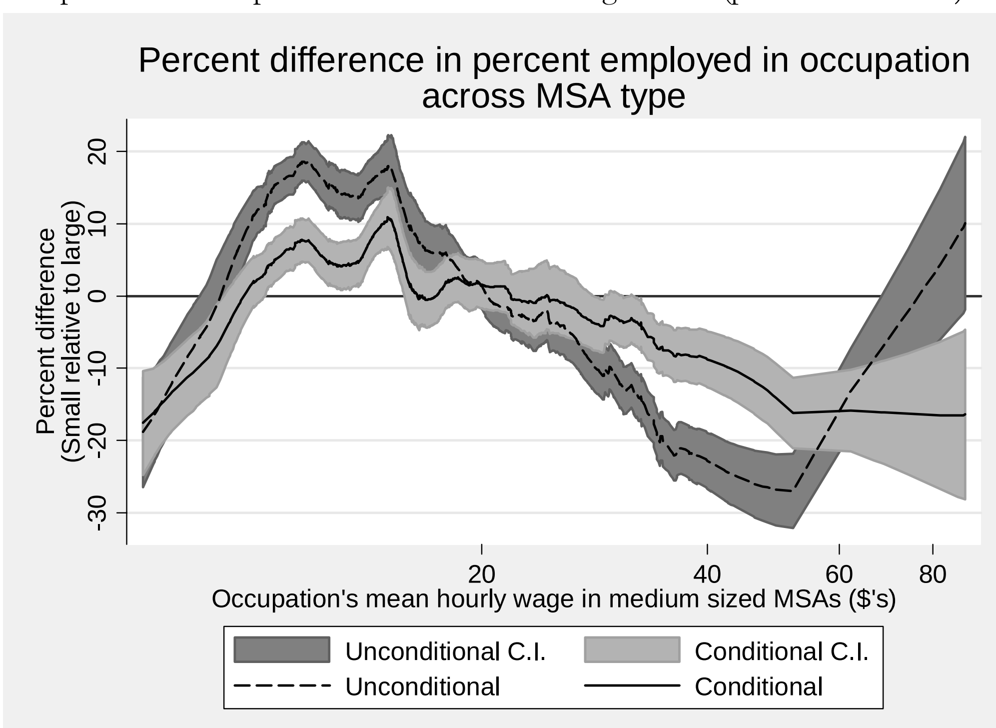


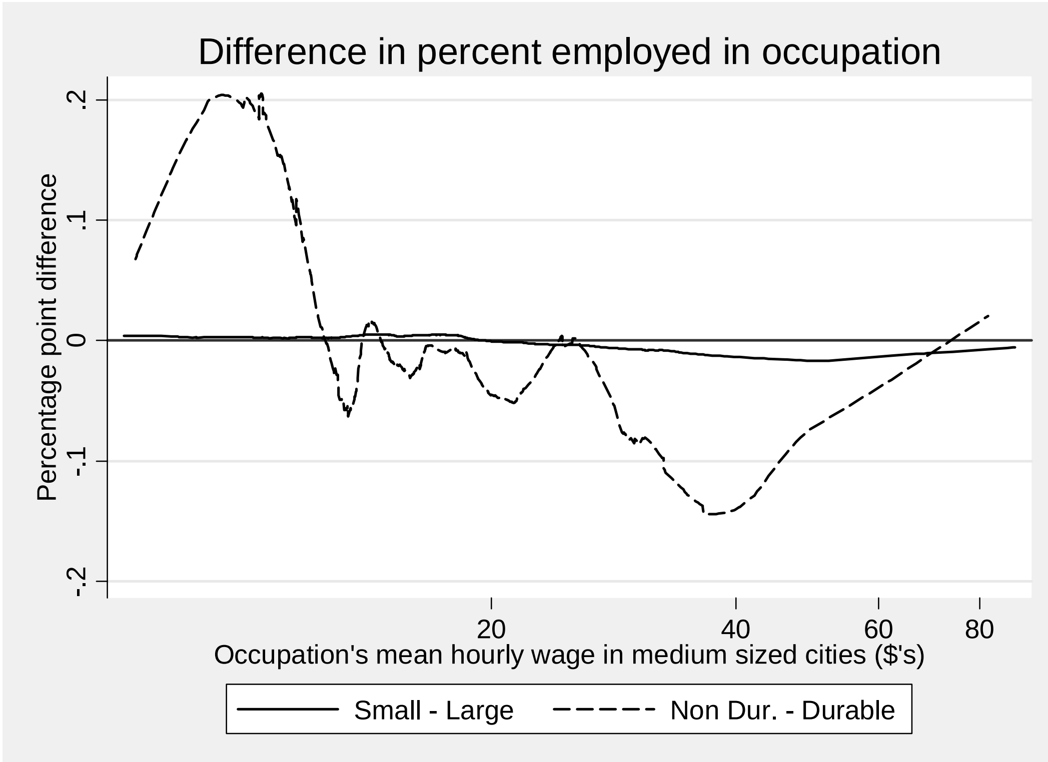
Figure 3: Comparison of occupational mix in small and large MSAs (percent difference)



Source for Figures 2 and 3: Authors calculations from OES micro-data

Notes for Figures 2 and 3: Shaded areas represent 95% confidence interval around smoothed difference in percent of employment in occupation across MSA type. Confidence intervals are derived from bootstrapped standard errors estimated with 200 replications. See Figure 1.

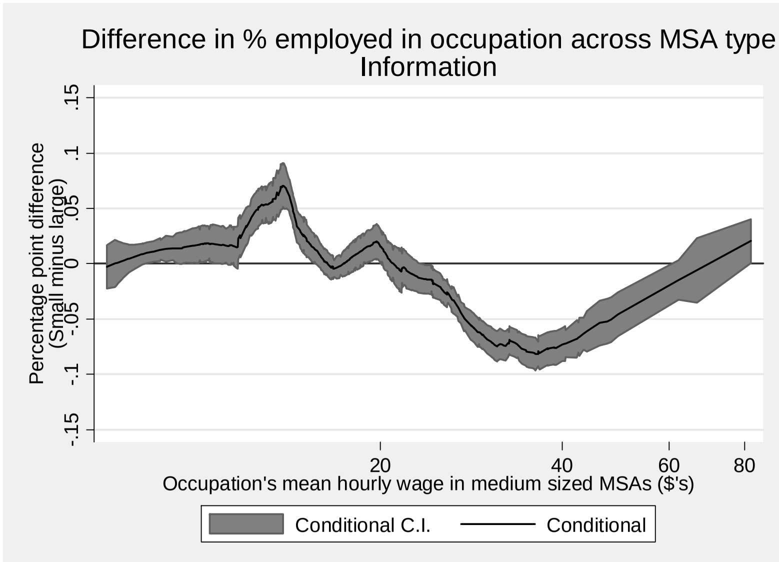
Figure 4: Comparison of differences in occupational mix between small and large MSAs and Non-Durable and Durable Manufacturing establishments



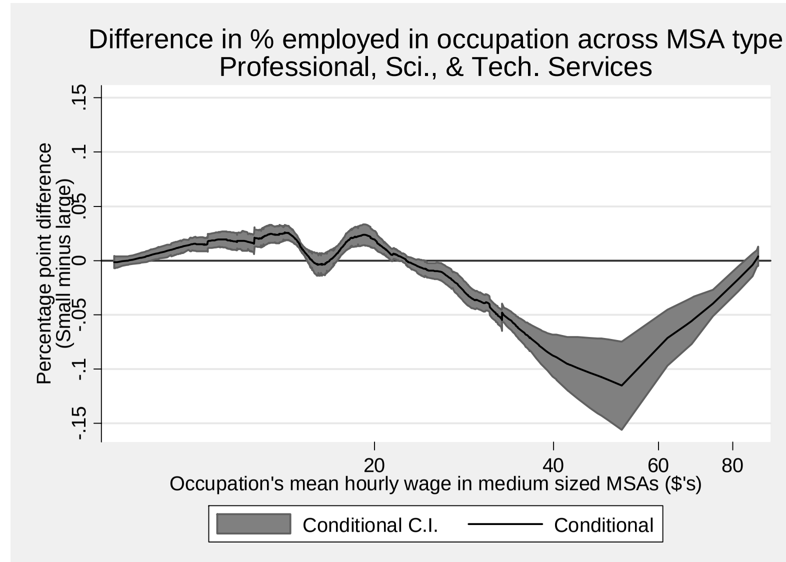
Source: Authors calculations from the OES micro-data.
Notes: Non-durable manufacturing is defined as all industries with NAICS codes that start with 31 or 32. Durable manufacturing is defined as all industries with NAICS codes that start with 33. See Figure 1.

Figure 5: Comparison of occupation mix for specific sectors

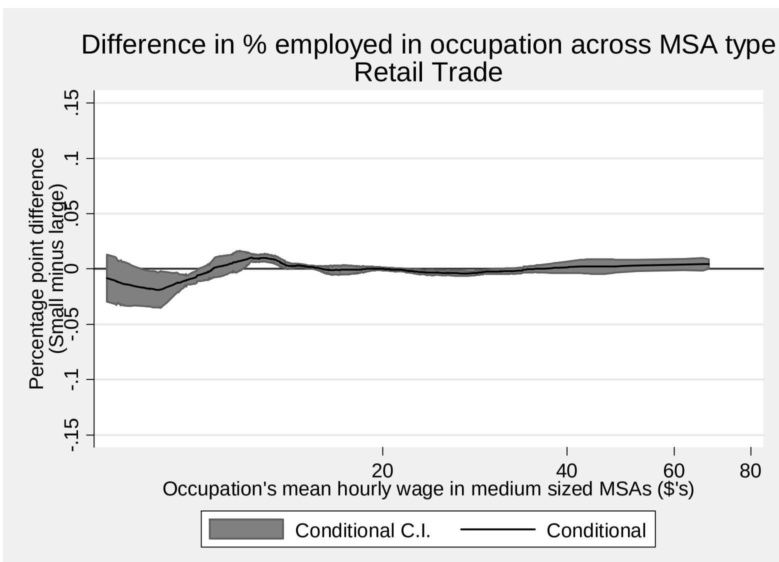
a. Information sector



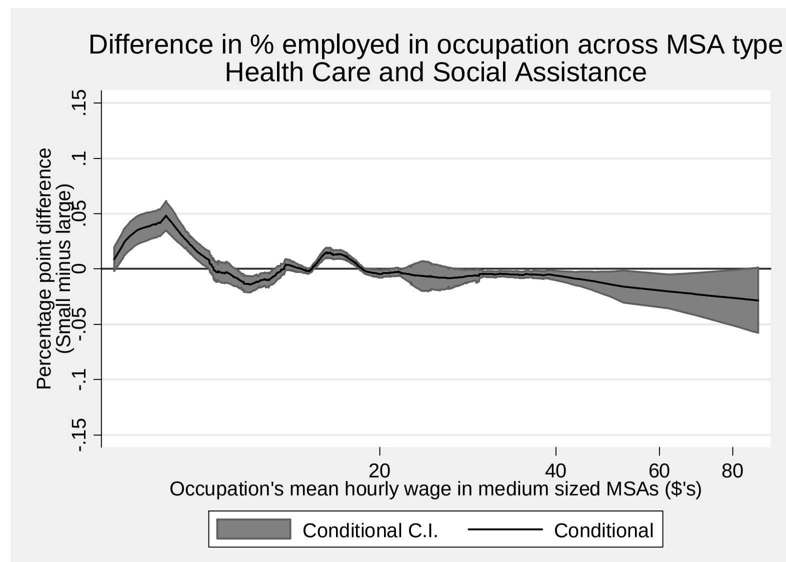
b. Professional, Scientific, and Technical Services sector



c. Retail Trade sector



d. Health Care and Social Assistance sector



Source: Author's calculations from OES micro-data.

Notes: See notes for Figures 1 and 2 and text.

Table 1: Classification of Metropolitan Statistical Areas into size groups

Name of Metropolitan Statistical Area	Population	Size rank	Size group
New York--Northern New Jersey--Long Island, NY--NJ--CT--PA CMSA	21,199,865	1	Large
Los Angeles--Riverside--Orange County, CA CMSA	16,373,645	2	Large
…			
Pittsburgh, PA MSA	2,358,695	21	Large
Portland--Salem, OR--WA CMSA	2,265,223	22	Large
Cincinnati--Hamilton, OH--KY--IN CMSA	1,979,202	23	Medium
Sacramento--Yolo, CA CMSA	1,796,857	24	Medium
…			
Oklahoma City, OK MSA	1,083,346	48	Medium
Louisville, KY--IN MSA	1,025,598	49	Medium
Richmond--Petersburg, VA MSA	996,512	50	Small
Greenville--Spartanburg--Anderson, SC MSA	962,441	51	Small
…			
Casper, WY MSA	66,533	275	Small
Enid, OK MSA	57,813	276	Small

Source: 2000 Census of Population and Housing

Table 2: Expository example of construction of skill intensity measure

Faux firms in NAICS 3327: Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing

	Number employed at		Difference in % of employment	Hypothetical medium wage
	Joe's	Precision	(Joe's - Precision)	(in $'s)
11-1021: General and Operations Managers	1	1	0.0%	40.00
43-5071: Shipping, Receiving, and Traffic Clerks	2	2	0.0%	11.25
43-6014: Secretaries, Except Legal and Medical, and Executive	1	1	0.0%	12.25
51-4011: Computer-Controlled Machine Tool Operators, Metal and Plastic	0	7	-58.3%	15.65
51-4012: Numerical Tool and Process Control Programmers	0	1	-8.3%	19.75
51-4031: Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	3	0	25.0%	13.00
51-4034: Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	4	0	33.3%	15.60
51-4041: Machinists	1	0	8.3%	17.00
Total employment	12	12		
Slope of difference in % on log medium wage				-0.0015

Table 3: Occupational employment by MSA type for selected occupations

Occupation	Mean wage in medium sized MSAs	Percent of employment in Small MSAs (1)	Percent of employment in Large MSAs (2)	Percent of employment in Large MSAs after condtioning (3)	(1) - (2) (4)	(1) - (3) (5)
Cashiers	8.10	3.043	2.656	3.065	0.387	-0.022
Construction Laborers	12.82	0.708	0.698	0.751	0.010	-0.043
Automotive Service Technicians and Mechanics	16.65	0.623	0.542	0.641	0.082	-0.018
Machinists	16.65	0.303	0.272	0.319	0.031	-0.016
Medical and Public Health Social Workers	19.27	0.091	0.087	0.098	0.004	-0.007
Electrical and Electronic Engineering Technicians	20.93	0.144	0.170	0.129	-0.026	0.015
Public Relations Specialists	22.56	0.118	0.148	0.117	-0.030	0.001
Credit Analysts	26.37	0.040	0.076	0.052	-0.036	-0.012
Architects, Except Landscape and Naval	28.61	0.064	0.101	0.067	-0.036	-0.002
Management Analysts	32.75	0.235	0.450	0.293	-0.215	-0.058
Economists	34.05	0.006	0.008	0.007	-0.003	-0.001
Electrical Engineers	34.47	0.117	0.151	0.112	-0.034	0.005
Lawyers	49.42	0.303	0.564	0.392	-0.261	-0.088
Internists, General	81.89	0.043	0.049	0.060	-0.006	-0.018

Source: Authors calculations from OES micro-data.

Notes: See Figure 1. "Percent of employment in …" is the percent of employment in the MSA type that is in the occupation.

Table 4: Skill intensity regression estimates

Dependent variable: occupation's percent of small MSA employment
Large MSAs data weighted to match the industry and size class distribution of small MSAs.

Sector	Log wage	% of large employment	Constant	Number of occupations
All sectors	-0.011	0.995	0.000	710
	(0.002)	(0.009)	(0.000)	
Information	-0.076	1.077	0.002	417
	(0.021)	(0.089)	(0.001)	
Utilities	-0.053	0.987	0.002	361
	(0.023)	(0.054)	(0.001)	
Professional, Scientific, and Technical	-0.041	0.950	0.001	612
Services	(0.011)	(0.045)	(0.000)	
Management of Companies and	-0.034	0.956	0.001	603
Enterprises	(0.011)	(0.039)	(0.000)	
Finance and Insurance	-0.033	1.034	0.001	422
	(0.009)	(0.017)	(0.000)	
Wholesale Trade	-0.031	0.925	0.001	569
	(0.010)	(0.033)	(0.000)	
Mining	-0.026	0.907	0.001	316
	(0.030)	(0.073)	(0.001)	
Arts, Entertainment, and Recreation	-0.021	1.006	0.001	469
	(0.015)	(0.041)	(0.000)	
Manufacturing	-0.017	1.020	0.000	602
	(0.006)	(0.027)	(0.000)	
Real Estate and Rental and Leasing	-0.016	0.960	0.001	495
	(0.015)	(0.023)	(0.000)	
Construction	-0.013	0.966	0.000	465
	(0.007)	(0.020)	(0.000)	
Health Care and Social Assistance	-0.012	1.007	0.000	571
	(0.007)	(0.021)	(0.000)	
Admin. & Support and Waste	-0.011	1.011	0.000	639
Management & Remediation Serv.	(0.005)	(0.024)	(0.000)	
Educational Services	-0.011	0.963	0.000	620
	(0.009)	(0.016)	(0.000)	
Retail Trade	-0.002	0.988	0.000	540
	(0.003)	(0.002)	(0.000)	
Other Services	-0.001	1.008	0.000	604
	(0.008)	(0.022)	(0.000)	
Transportation and Warehousing	0.021	1.114	-0.001	525
	(0.015)	(0.087)	(0.000)	
Accomodation and Food Services	0.022	1.026	-0.001	392
	(0.011)	(0.014)	(0.000)	

	Log wage	% of durable employment	Constant	Number of occupations
Non-durable relative to durable	-0.155	0.535	0.005	602
manufacturing	(0.043)	(0.087)	(0.001)	

Source: Authors calculations from OES micro-data

Notes: Each pair of rows represents a different regression. The unit of observation is an occupation. "Log of Medium Wage" is the natural log of the mean wage in the occupation in medium sized MSAs. See text for more details.