An Inter-urban Wage Test of the Monocentric Model

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Abstract: We present a simple test of the monocentric model based on variations in inter-urban wage differentials by occupation. We classify occupations as more or less central according to the density of employment where job holders in those occupations work. Our conjecture is that more central occupations receive differentially higher wages in larger cities, since workers in those occupations face a less desirable locus of housing prices and commuting times than those who have jobs in residential areas. The results presented in the empirical section are consistent with this hypothesis, and they are robust to the inclusion of individual-specific human capital variables and city-specific controls. These findings have implications for inter-urban cost of living indexes, where wages are used to approximate the true cost of living.

This version: March 2007

JEL codes: J31, R12

Keywords: monocentric model; wage differentials; wage gradients

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1. Introduction

The theory of spatial compensating wage differentials developed along two paths. Inter-urban variation relies on the Rosen-Roback model (Rosen 1979, Roback, 1982, 1988) which explains rent and wage variations across cities in terms of intrinsic city characteristics, defined broadly as amenities (consumptive or productive). In these models workers require higher salaries in larger cities to offset paying higher housing prices or rent at a given consumptive amenity level. Similarly, at a given productivity level, firms would offer lower wages in larger cities to offset higher rents. Of course, firms may be willing to pay both higher wages and rent in larger cities if productivity is also higher due to agglomeration economies.

The traditional intra-urban wage theory was built around the Alonso-Muth-Mills monocentric model where residents choose their proximity to the CBD trading higher rents against shorter commuting times (Alonso, 1962, Muth, 1969 and Mills, 1972; Brueckner, 1987, Straszheim, 1987 and White, 1999 provide excellent reviews). Extensions of the model incorporated local employment and multiple centers (see Solow, 1973 and White 1988). The simplest models developed along these lines predict that rent and wages decline with distance from the CBD (see White, 1988 and 1999).

Empirical evidence confirms in general the existence of wage gradients, that is, wages decline when the job location becomes more suburbanized. Eberts (1981), Ihlanfeldt (1992) and McMillen and Singer (1992) find surprisingly strong support for the hypothesis that wages for otherwise similar jobs decline with distance from the CBD.

However, Glaeser and Kahn (2001) argue that the decentralization of employment has eroded the wage gradient, and therefore, monocentric models no longer represent intra-urban wage patterns. They argue that in modern cities, employment location tracks reasonably well where the workers live, possibly to adjust to workers' preferences. Alternative models were built to allow for polycentric employment cities, where several employment centers may arise simultaneously (a general discussion about the modern urban structure can be found in Anas, Arnott and Small, 1998).

The process of decentralization is far from homogeneous. While services and idea-intensive industries are likely to be centralized, manufacturing tends to sprawl within cities (Glaeser and Kahn, 2001). Empirical studies have not yet systematically analyzed the concentration patterns in terms of occupation. Analyzing decentralization by occupation is a reasonable alternative since the same firm may have its different processes in different places in the city, or even in different cities. On the one hand, Lawyers or administrative and financial services workers may have offices located in the CBD. On the other hand, production workers, teachers or veterinarians may be more spread across neighborhoods. Workers in occupations that have a higher likelihood of working downtown will face a less desirable locus of combinations of housing prices and commuting times than those who have jobs in residential areas. This difference is expected to be enhanced in bigger cities where housing prices are higher (very high in the CBD) and commuting costs are greater. That is, while all workers in large cities will receive a compensating differential if city size increases commute times and housing prices, the relative premium will be larger for occupations in which the likelihood of working nearer the CBD is higher.

Overall this constitutes a monocentric representation of a polycentric world which can be easily tested[2]. Interpreting an index of occupational centrality (constructed as a relative average employment density measure by occupation) as a measure of closeness to the CBD, we test for higher inter-city compensating wage differentials for city size in more central occupations. Strictly speaking we are not testing the validity of the simplest monocentric models, in which all employment occurs in the CBD, but Solow's (1973) model that contains both CBD and local employment.[3]

Arguably, centrality premiums may be the result of either higher compensation for higher rents and commuting times, ability sorting, or differences in productivity across cities (i.e. agglomeration economies). While we are testing for differential city size premiums across occupations of varying centrality, is it still possible that those individuals who stand to gain more productivity from increases in city size sort into more central occupations and larger cities. Unfortunately data limitations impede our fully distinguishing among competing explanations. However, our empirical strategy is intended to isolate the effect of higher housing costs and commute times in central

[2] We oversimplify the discussion about the relation between the monocentric and polycentric models. For a theoretical discussion on how monocentric aggregates translate into polycentric ones sees Arnott (2001).
[3] We are in debt to Richard Arnott for this insight.

occupations in larger cities on compensation. First, the results presented in the empirical section are robust to the inclusion of human capital variables in addition to occupation controls which reduce the potential effects of individuals sorting across cities and occupations. Second, the inclusion of city specific dummy variables controls for amenity and productivity effects.

The objectives of the paper are three-fold. First, the paper constitutes a simple test of the continuing usefulness of the monocentric model. Second, we address whether a measure constructed in line with the monocentric model, occupation centrality, contributes to explaining inter-urban wage differentials. Third, the findings in the model have implications for the construction of inter-urban cost of living indexes, where wages are used to approximate the true cost of living.

2. Some stylized facts and main hypothesis

As suggested in the Introduction, if an occupation is central, then its workers face a less favorable trade-off between commuting time and high rents, and as a result wage premiums should increase more with city size relative to non-central occupations. As an example, consider lawyers (OCC 210) who rank at the top of occupations in terms of centrality (see Table 4 below) and production workers (OCC 770 to 899), who are in the least central occupation categories. Also consider the relative city-occupation wage premium constructed as $\frac{\overline{w}_{c,L}}{\overline{w}_{c,P}}$, where $\overline{w}_{c,j}$ denotes the average wage in city c and occupation j (*=L: lawyers, P: production workers)* (see the following section for details about how these variables were constructed).

Figures 1 and 2 report the relative wage premiums as a function of city size where city size is measured by the logarithm of total employment and average commuting time respectively. The figures show that the relative premium increases with both measures of city size. We attribute this to differences in the occupation centrality, that is to the fact that lawyers are more likely to work in the CBD (and therefore require a higher relative compensation in large cities) than production workers. The empirical analysis below shows that this result can be extended to all occupations, and that it is robust to the inclusion of additional controls.

In order to understand the usefulness of this result, consider the example of a generic firm that is considering moving to a city which exactly doubles the employment size. Moreover, assume that this firm has two types of workers, legal and production workers, and that it seeks for the right compensation scheme to keep its employees exactly indifferent between working in the small and the big city. In both cities, lawyers would be working in its downtown office and production workers in its outskirts assembly plant. The firm needs to adjust wages in order to compensate its workers for the higher cost of living or higher commuting time, but should the firm adjust wages equally for all occupations? The results in Section 4 imply that legal workers, a typical central occupation, should receive a higher premium than production workers. In other words, intra-firm wage differences will increase as a result of moving to a larger city.

Are these figures the result of a more general pattern? In order to answer this question we run a simple regression model for each occupation category, where the log of the average wage in each MSA is regressed against a measure of city size. In particular, we consider the logarithm of the total employment and average commuting time. In each case we obtain 475 regression coefficients (one for each occupation) and we plot them against the centrality index constructed as in the following section. The positive relations depicted in Figures 3 and 4 confirm the hypothesis that more central occupations receive higher premiums in larger cities (with logarithm of employment t-stat=5.84, R^2=0.07; with average commuting time t-stat= 6.73, R^2=0.09).

3. Occupation centrality and data description

The 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series (IPUMS) provides detailed information about household location at the level of Public Use Micro Areas (PUMA) which consist of counties or portions of counties with populations of at least 100,000. The corresponding information about workplace location is available only at a coarser level, Place of Work Public Use Micro Areas (PWPUMA). One PWPUMA may contain several PUMAs. Following Timothy and Wheaton (2001), the centrality index is constructed using those cities which contain several PWPUMA (at least ten) and smaller compact center city jurisdictions, except those with very strong concentration in a single PWPUMA, such as Los Angeles or New York, where more than 50% of employment is located in a single PWPUMA. The cities selected were Atlanta, Boston, Detroit, Philadelphia, Pittsburgh, Minneapolis and Washington. The selection covers old historical cities like Boston, modern cities like Minneapolis, administrative MSAs like Washington and an MSA with an especially poor CBD like Detroit[4]. We use these seven cities to construct a centrality index for every occupation category.

Let the PWPUMAs in the MSA c be indexed by i. Let E_i denote employment and A_i denote the area of a given PWPUMA. The employment density in the PWPUMA can be calculated as $\lambda_i = \frac{E_i}{A_i}$ which measures the number of workers per area unit (i.e. workers per square mile). Moreover, the share of the MSA employment that has workplace in the PWPUMA can be calculated as $\omega_i = \frac{E_i}{E_c}$, where E_c denotes the total employment in the MSA c. Moreover, for each occupation j, let $\omega_{ij} = \frac{E_{ij}}{E_{cj}}$ denote the share of the total employment of that occupation with workplace in the PWPUMA i. The average employment density of the MSA can be calculated as $\sum_{i \in c} \lambda_i \omega_i$. If occupation j is central (i.e. more likely to be located in highly dense areas than the average worker in the city) then we should have that $\sum_{i \in c} \lambda_i \omega_{ij} > \sum_{i \in c} \lambda_i \omega_i$; while a non-central occupation should have $\sum_{i \in c} \lambda_i \omega_{ij} < \sum_{i \in c} \lambda_i \omega_i$. Therefore, a centrality index can be constructed as:

$$(1) \qquad K_{cj} = \frac{\sum_{i \in c} \lambda_i \omega_{ij}}{\sum_{i \in c} \lambda_i \omega_i}$$

[4] Brueckner, Thisse and Zenou (1999) claim that "an urban area like Detroit lacks the rich history of Paris, the central-city's infrastructure does not offer appreciable aesthetic benefits. This means that no amenity force is working to reverse the conventional forces that draw the rich to the suburbs. As a result central Detroit is poor." (p.94)

The index has domain on the non-negative real numbers[5] and represents the relative employment density of the occupation with respect to the total employment density. For each city, the weighted average K is 1. Thus, an occupation that follows the total employment pattern should have a value of 1. Moreover, an occupation that is likely to be located in a PWPUMA with high employment density (i.e. central) should have a value above 1; while an occupation mostly located in the outskirts of the city (non-central) should have a value below 1.

Our occupation centrality measure K is not constructed as in other empirical studies as the distance with respect to the CBD (for instance Eberts, 1981; Ihlanfeldt, 1982; Glaeser and Kahn, 2001), but as an average employment density measure. Three reasons can be named for this construction. First, we allow for the existence of multiple employment centers, and we construct a measure indicating the degree of whether a certain occupation is more likely to be located in high/low employment density PWPUMAs than the total employment pattern in the city. Therefore, the centrality measure is not affected by the selection of the CBD. Second, distance to the CBD is an isotropic measure (i.e. the same in all directions) which implies that it cannot account for the specific geographical patterns of the city. Using the PWPUMA structure allows for more geographical flexibility in this sense. Third, the irregular PWPUMA structure does not allow us to accurately measure the distance from the city's CBD.

For each occupation we construct a centrality index (*K*) which is defined as the simple average for all the cities considered above. To illustrate how the index is constructed, figures 5 and 6 depict λ_i and ω_i for Boston and Minneapolis respectively, and they show the intuition behind the *K* index. It is observed that for both cities, more colored (which represent higher density) areas generally correspond to the traditional CBD in terms of λ_i, although a different pattern emerges in terms of ω_i. Moreover, changes in λ_i and ω_i are not isotropic with respect to the CBD, that is, they are not uniform in all directions. Similar patterns can be observed for the rest of the cities used for the construction of K.

The indexes are constructed for each occupation in the SOC category (475 categories) and for each of the seven MSAs, except for those occupations and MSAs with

[5] Undefined for $E_{cj}=0$.

no workers (i.e. $E_{cj} = 0$). Table 1 presents pairwise correlation coefficients for the cities used in this study. For all cases we observe a positive and significant correlation, with a minimum value corresponding to the comparison Detroit-Philadelphia (0.26) and a maximum corresponding to Boston-Minneapolis (0.55). The constructed average has a minimum correlation with Detroit (0.48) and a maximum with Pittsburgh (0.80). Table 2 reports the pairwise Spearman rank correlation estimates. The same pattern found for the raw correlation is observed in terms of ranks. As an illustrative example of the positive relation of the K indices across MSAs, Figure 7 plots the *K* indices for Boston and Minneapolis. Finally we calculate the Kendall coefficient of concordance to test the degree of association among the rank correlations: using 445 occupations available in all the MSAs we obtain a highly significant value of 0.55.

These findings suggest strong similarities across MSAs for the set of occupations, which may reveal the existence of a single scalar index which sorts occupations according to their intrinsic *centrality* value. In fact, principal component factor analysis (Table 3) shows that only one factor is behind the concentration indices across MSAs. The factor loadings follow closely the correlation of the average K for the MSAs considered here and the MSA specific index. For this reason we use the average K as the overall centrality measure by occupation.

Table 4 reports average *K* and ranks for major SOC occupations. Lawyers and entertainers are the occupations which have the highest K index value, while agricultural and production workers appear at the opposite extreme. Within the major categories we also observe a large dispersion in the education related categories. This is likely because professors and teachers are very dissimilar occupations, despite belonging to the same broad classification category. Although not reported, we also calculate the statistics of Table 4 for men and women separately. Certain occupations have considerable changes depending on the sub-sample used to calculate the centrality index. For instance, teachers and nurses became more centralized if only men are considered. This result is explained by the fact that women are more likely to prefer to work in the outskirts of the city, near where they live.

For each of the 272 MSAs in the 5% Sample of the US 2000 Census we take all individuals in the 25-65 age range who are employed (either salaried or self-employed), working at least 20 hours per week. In addition, we construct individual annual gross wages (in logs, log *w*), average weekly hours worked (in logs, log *hours*), gender (FEM), education (years of schooling, *EDUC*), age (*AGE*), and dichotomous variables for black workers (BLACK) and Hispanic origin (*HISP*). City size is measured by the logarithm of aggregate employment (log *E*; only individuals who satisfy the criteria defined above). Finally we also compute the average city commuting time (*COM*). For computational purposes, we take a 30% random sample of the 5% Sample US 2000 Census when dummies by state are used and a 5% random sample when MSA dummies are used.

4. Econometric analysis

The simple hypothesis suggested above predicts that more central occupations receive higher premiums in larger cities. That is, central occupations should have a higher premium in bigger cities, after controlling for city and occupation characteristics. In order to study the validity of this hypothesis, we consider a fixed effects baseline model of the form:

$$(2) \qquad \log w_{i,cj} = \alpha\left(K_j \times \log E_c\right) + \beta X_i + \eta_c + \mu_j + \varepsilon_i$$

η and μ denote MSA specific and SOC specific fixed effects respectively, and ε denotes an individual i.i.d. error component. *X* is a set of human capital and other individual specific variables. Therefore, the parameter of interest is α, which tells us whether central occupations earn higher premiums in bigger cities. Moreover α is orthogonal to potential ability sorting coming from individuals sorting across cities according to their unmeasured ability (i.e. some cities attract the best/worst workers in each occupation) as this effect is captured by MSA-specific controls. Table 5 reports the regression results for model (2) using different specifications. All specifications contain dummies for each SOC occupation category (475 categories). The first three columns have dummies by state, and the last two columns contain dummies by MSA. In the former case, we also include log *E* as a freestanding variable[6].

For all the cases considered in the table we observe a positive and significant coefficient estimate of K× log E[7]. The coefficient of interest is 0.0719 if only log *E* and state and occupation dummies are included as controls (column 1); including individual specific human capital variables decreases it to 0.0537 (column 2); and it is reduced to 0.0467 (column 3) if the average commuting time is included as an additional covariate. Our results corroborate Timothy and Wheaton's (2001) findings regarding compensation for average commuting time: adding 10 minutes to the average commuting time increases wages by 10%.

Inclusion of MSA-specific dummy variables controls for any invariant city specific characteristics that might affect wages, such as amenities or local government fiscal policy, in addition to commuting time, aggregate employment, and invariant state characteristics. In this case the centrality effect becomes 0.0732 and 0.0551 without and with human capital controls, respectively (sees Table 5, columns 4 and 5). Overall, these results confirm our hypothesis that workers in more central occupations are likely to receive larger premiums for living in larger cities, and that these premiums are not compensation for more (*observable*) human capital.

To see how to interpret the coefficient of interest, we return to the generic firm example developed in Section 2, and calculate how the changes in the wages of legal and production workers would differ in the case that the firm moves to a city that doubles its employment size. The increase in the logarithm of wages for a given occupation is simply $\alpha K \log(2)$. From Table 4 we get that these occupations have centrality indices of 1.48 and 0.756 respectively. Using the coefficient from the model with MSA and human capital controls, the increase in the log wages of legal workers should exceed the increase in the log wages of production workers by $0.0551(1.48\text{-}0.756)\log(2)$, or about 3%.

We also explore how the effect of centrality on wages changes by gender. To the extent that women are more likely to devote more time to child care, they will place more

[6] This specification assumes that the MSA-specific fixed effect can be decomposed in a state fixed-effect and city-size premium.

[7] Although not reported, similar results are obtained when K × COM is used instead of K × log E, that is, when commuting time is used as a *proxy* of city size. Moreover, the results are essentially identical if the log of the centrality index is interacted with log employment.

value on time away from work. Consequently, women might prefer to live near their residences and should therefore receive higher compensation for long commuting times to the CBD. The gender dummy variable is interacted with K× log *E*, and the results of the new regressions appear in Table 6. As expected, women are more responsive to the occupation's centrality value. Although not reported we do not find significant differences by race or Hispanic origin.

6. Implications for wage indexes

Comparable wage approaches to differences in cost-of-living attempt to construct an index of what it takes to attract workers of comparable quality across geographic areas. As a first approximation to this problem, consider estimating equation (2) without including the centrality variable. In that case, the predicted market wage in city *c* across cities for a given occupation *j* can be estimated by:

$$(3)\quad \log \hat{w}_{cj} = \hat{\beta} X_j + \hat{\eta}_c + \hat{\mu}_j$$

The hypothesis in this paper predicts that occupation centrality may affect the estimation of both η_c and μ_j. First, the MSA-specific effect will be upward (downward) biased if the city's occupation mix is skewed towards central (non-central) occupations. Second, the occupation-specific effect will also be upward (downward) biased if it is a central (non-central) occupation.

Consider the general problem of constructing a compensation scheme for public employees in a non-central occupation (e.g. teachers) across different cities. Without controlling for centrality, non-central (central) workers living in a large city would receive more (less) compensation than the minimum they are willing to accept for working there and the opposite would hold in small cities. This is because, as a non-central occupation, they do not face the steep rent gradients more central occupations do. In that case, a better estimate would be given by the predicted wage of an average teacher using the full equation (2):

$$(4)\ \log \hat{\hat{w}}_{cj} = \hat{\hat{\alpha}}\left(K_j \times \log E_c\right) + \hat{\hat{\beta}} X_j + \hat{\hat{\eta}}_c + \hat{\hat{\mu}}_j$$

Using the baseline specification of Table 5, column 5, we compute the difference between both approaches, that is $\log \hat{\hat{w}}_{cj} - \log \hat{w}_{cj}$, for elementary and middle school teachers (OCC 231; assumed to be a white non-Hispanic woman, age 40, with a bachelor's degree). These differences are plotted in Figure 8. As expected, the figure shows a negative relation between $\log \hat{\hat{w}}_{cj} - \log \hat{w}_{cj}$ and the city's log of total employment. In other words, a compensation scheme based on equation (4) would produce lower (higher) wages in large (small) cities as compared to equation (3). Thus, ignoring the affect of occupational centrality would lead to a compensation scheme in which schools in small cities could not compete as effectively as schools in large cities for teachers of the same quality.

7. Conclusions and suggestions for future research

We find suggestive evidence that indicates that central occupations, defined as those occupations which are more likely to have a workplace location in high employment density areas, receive higher premiums relative to non-central occupations in larger cities. The intuitive idea behind this finding is that workers in central occupations face a less desirable locus of combinations of housing prices and commuting times than those in non-central occupations, which is a simple application of a monocentric model of intra-urban wage differentials with decentralized employment. As stated by Crampton (1999), to a great extent, applied urban labor market research has been data-driven. Therefore, the empirical evidence presented in this paper should guide researchers on the search for an integrated theory of inter and intra urban wage differentials.

Compensation schemes should take into account centrality as an important determinant of wage differentials. In particular, if our objective is the construction of a regional wage index, which is constructed using aggregate information on a considerable number of occupations, wage differentials should take into account the *centrality* attribute of each occupation. Moreover, the pure amenity and productivity effects should be separated from the centrality premium if they are to be estimated accurately.

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Table 1 – Pairwise correlation coefficients of the centrality indexes

	Average	Atlanta	Boston	Detroit	Minneapolis	Philadelphia	Pittsburgh	Washington
Average	1.000 475							
Atlanta	0.645 473	1.000 473						
Boston	0.753 469	0.500 468	1.000 469					
Detroit	0.485 464	0.306 462	0.284 459	1.000 464				
Minneapolis	0.767 459	0.479 459	0.545 457	0.378 454	1.000 459			
Philadelphia	0.668 471	0.361 470	0.518 467	0.259 462	0.449 458	1.000 471		
Pittsburgh	0.800 468	0.427 467	0.423 463	0.336 460	0.504 455	0.360 466	1.000 468	
Washington	0.777 468	0.503 467	0.531 464	0.268 459	0.524 432	0.482 466	0.487 463	1.000 468

Notes: Each cell contains the pairwise correlation coefficient of the centrality indexes and the number of occupations used.

Table 2 – Pairwise Spearman rank correlation coefficients of the centrality indexes

	Average	Atlanta	Boston	Detroit	Minneapolis	Philadelphia	Pittsburgh	Washington
Average	1.000 475							
Atlanta	0.674 473	1.000 473						
Boston	0.769 469	0.557 468	1.000 469					
Detroit	0.503 464	0.383 462	0.315 459	1.000 464				
Minneapolis	0.777 459	0.564 459	0.565 457	0.401 454	1.000 459			
Philadelphia	0.682 471	0.424 470	0.527 467	0.286 462	0.494 458	1.000 471		
Pittsburgh	0.799 468	0.453 467	0.459 463	0.368 460	0.534 455	0.429 466	1.000 468	
Washington	0.788 468	0.563 467	0.592 464	0.307 459	0.559 454	0.487 466	0.519 463	1.000 468

Notes: Each cell contains the pairwise Spearman rank correlation coefficient of the centrality indexes and the number of occupations used in each pair.

Table 3 - Principal components factor analysis

Factors	Eigenvalue	Difference	Proportion	Cumulative
1	3.117	3.016	1.126	1.126
2	0.101	0.112	0.036	1.163
3	-0.011	0.050	-0.004	1.159
4	-0.061	0.015	-0.022	1.136
5	-0.076	0.052	-0.028	1.109
6	-0.129	0.044	-0.046	1.062
7	-0.172	-	-0.063	1.000

Variable	Factor 1	Factor 2	Uniqueness
Atlanta	0.683	0.008	0.534
Boston	0.729	-0.137	0.449
Detroit	0.473	0.187	0.741
Minneapolis	0.731	0.034	0.463
Philadelphia	0.634	0.133	0.581
Pittsburgh	0.668	0.158	0.529
Washington	0.715	-0.058	0.485

Table 4

Centrality by occupation category

SOC category	Category of Occupation	Rank	K	Atl	Bos	Det	Minn	Phil	Pitts	Wash
23	**Legal**	1	1.480 (0.163)	2	1	4	1	1	2	1
27	**Arts, Design, Entertainment, Sports and Media**	2	1.332 (0.183)	3	3	3	2	3	6	3
15	**Computer and Mathematical**	3	1.274 (0.165)	1	4	1	6	12	3	4
19	**Life, Physical, and Social Science**	4	1.235 (0.322)	6	2	5	4	11	4	9
55	**Military Specific**	5	1.233 (0.212)	4	10	6	20	23	1	2
13	**Business and Financial Operations**	6	1.198 (0.252)	5	7	2	5	13	5	5
33	**Protective Service**	7	1.180 (0.235)	20	8	9	3	2	7	6
25	**Education, Training and Library**	8	1.110 (0.395)	14	9	10	7	6	9	8
21	**Community and Social Services**	9	1.102 (0.158)	7	5	14	12	4	8	11
43	**Office and Administrative Support**	10	1.072 (0.193)	10	12	7	10	9	12	10
29	**Practitioners and Technical**	11	1.061 (0.234)	11	14	8	9	5	10	17
11	**Management**	12	1.037 (0.352)	8	15	12	11	14	11	7
35	**Food Preparation and Serving**	13	0.972 (0.088)	17	13	15	13	8	17	12
39	**Personal Care and Service**	14	0.965 (0.317)	16	11	20	19	7	15	13
17	**Architecture and Engineering**	15	0.955 (0.318)	9	16	18	16	18	13	16
53	**Transportation and Material Moving**	16	0.946 (0.288)	13	6	19	14	10	22	14
31	**Healthcare Support**	17	0.922 (0.110)	15	18	22	8	16	18	15
41	**Sales and Related**	18	0.903 (0.179)	12	17	11	15	17	14	19
37	**Grounds Cleaning and Maintenance**	19	0.872 (0.204)	18	20	21	21	15	16	18
49	**Installation, Maintenance and Repair**	20	0.811 (0.149)	19	21	17	17	21	20	21
47	**Construction and Extraction**	21	0.764 (0.240)	21	19	23	22	20	19	20
51	**Production**	22	0.756 (0.232)	23	22	13	18	19	21	23
45	**Farming, Fishing, and Forestry**	23	0.638 (0.434)	22	23	16	23	22	23	22

Notes: Standard errors in parenthesis.

Table 5

Dep.Var. log Wage	(1)	(2)	(3)	(4)	(5)
K × log E	0.0719***	0.0537***	0.0467***	0.0732***	0.0551***
	(0.0025)	(0.0022)	(0.0023)	(0.0063)	(0.0056)
log E	-0.0212***	-0.0045*	-0.0279***		
	(0.0025)	(0.0022)	(0.0023)		
FEM		-0.2172***	-0.2167***		-0.2205***
		(0.0015)	(0.0015)		(0.0037)
EDUC		0.0485***	0.0482***		0.0477***
		(0.0003)	(0.0003)		(0.0008)
AGE		0.0810***	0.0810***		0.0811***
		(0.0003)	(0.0003)		(0.0007)
AGE^2/100		-0.0800***	-0.0800***		-0.0803***
		(0.0003)	(0.0003)		(0.0008)
BLACK		-0.0887***	-0.0919***		-0.0885***
		(0.0020)	(0.0020)		(0.0050)
HISP		-0.0949***	-0.0981***		-0.0924***
		(0.0022)	(0.0022)		(0.0055)
log hours		0.9683***	0.9671***		0.9545***
		(0.0032)	(0.032)		(0.0079)
COM			0.1048***		
			(0.0024)		
Controls:					
STATE	YES	YES	YES	NO	NO
MSA	NO	NO	NO	YES	YES
SOC	YES	YES	YES	YES	YES
Obs.	1,154,547	1,154,547	1,154,547	192,469	192,469

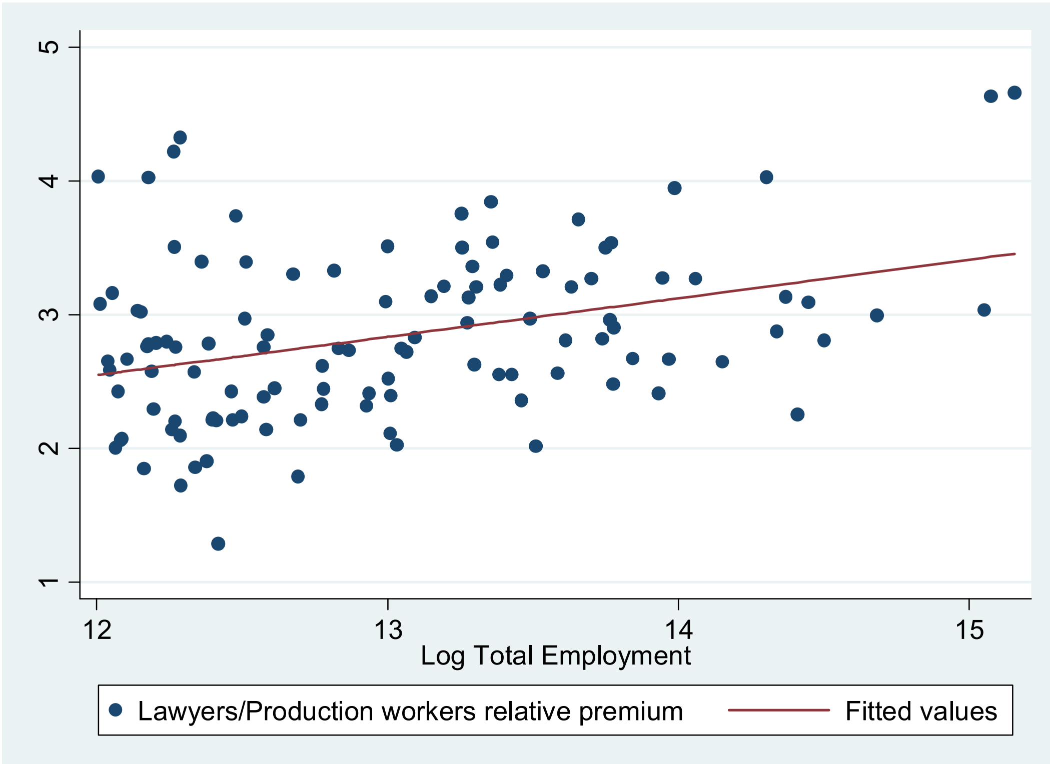
Notes: Standard errors in parenthesis. * significant at 10% level, ** significant ant 5% level, ***significant at 1% level. Authors' calculations using 5% Sample of 2000 Census from IPUMS. Columns 1-3 use a 30% random sample; columns 4-5 use a 5% random sample.

Table 6

Dep.Var. log Wage	(1)	(3)
K × log E	0.0483***	0.0498***
	(0.0023)	(0.0056)
log E	-0.0026	
	(0.0022)	
FEM	-0.3172	-0.3145***
	(0.0058)	(0.0143)
FEM×K×E	0.0075***	0.0071***
	(0.0004)	(0.0010)
EDUC	0.0485***	0.0477***
	(0.0003)	(0.0008)
AGE	0.0811	0.0811***
	(0.0003)	(0.0007)
AGE^2/100	-0.0800***	-0.0803***
	(0.0003)	(0.0008)
BLACK	-0.0892***	-0.0889***
	(0.0022)	(0.0050)
HISP	-0.0949***	-0.0925***
	(0.0022)	(0.0054)
log hours	0.9679***	0.9540***
	(0.0032)	(0.0079)
Controls:		
STATE	YES	NO
MSA	NO	YES
SOC	YES	YES
Obs.	1,154,547	192,469

Notes: Standard errors in parenthesis. * significant at 10% level, ** significant ant 5% level, ***significant at 1% level. Authors' calculations using 5% Sample of 2000 Census from IPUMS. Columns 1-3 use a 30% random sample; columns 4-5 use a 5% random sample.

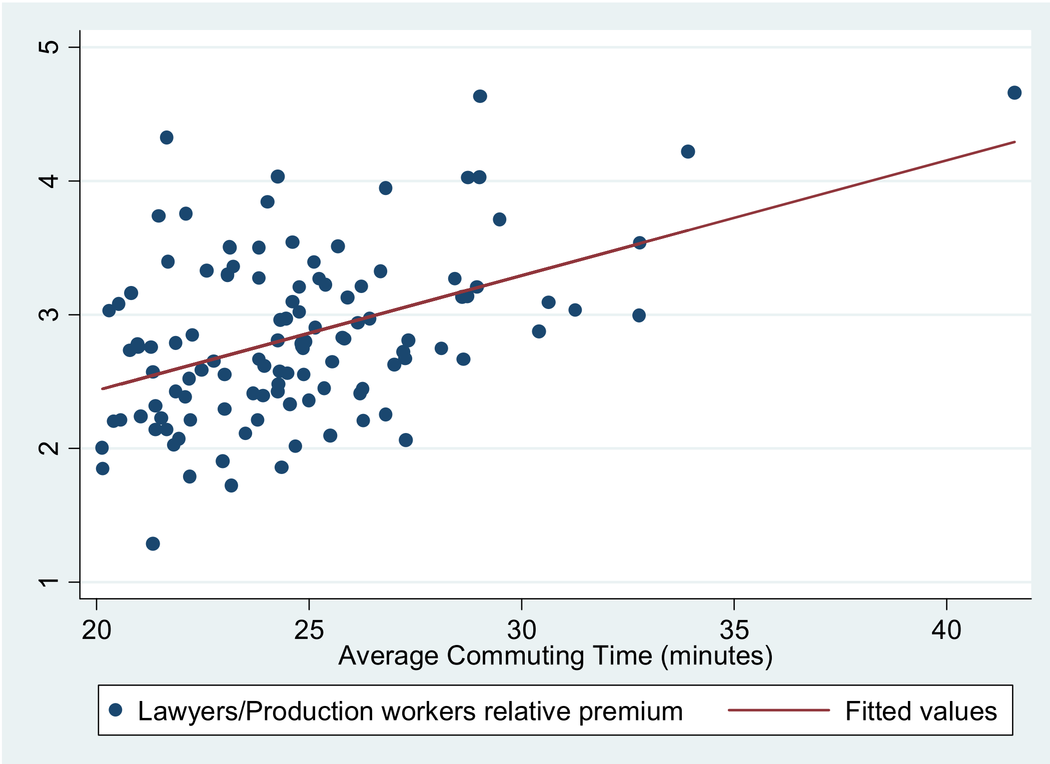
Figure 1



Title: Lawyers/Production workers relative premium and log of total employment

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.

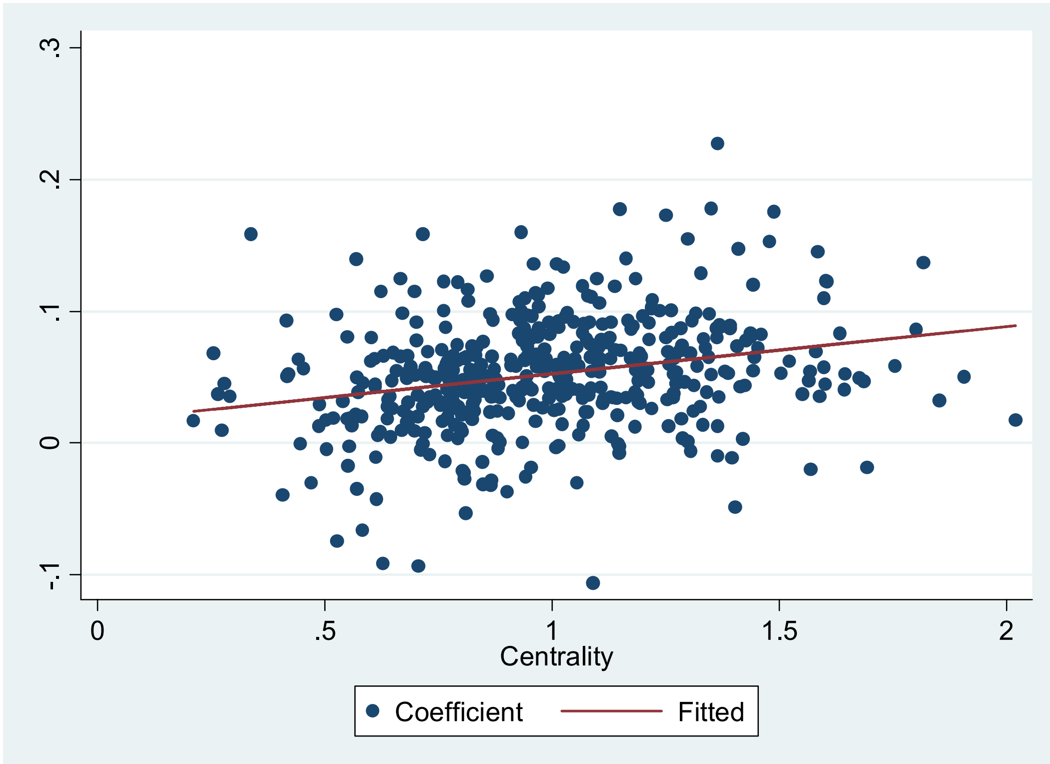
Figure 2



Title: Lawyers/Production workers relative premium and average commuting time

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.

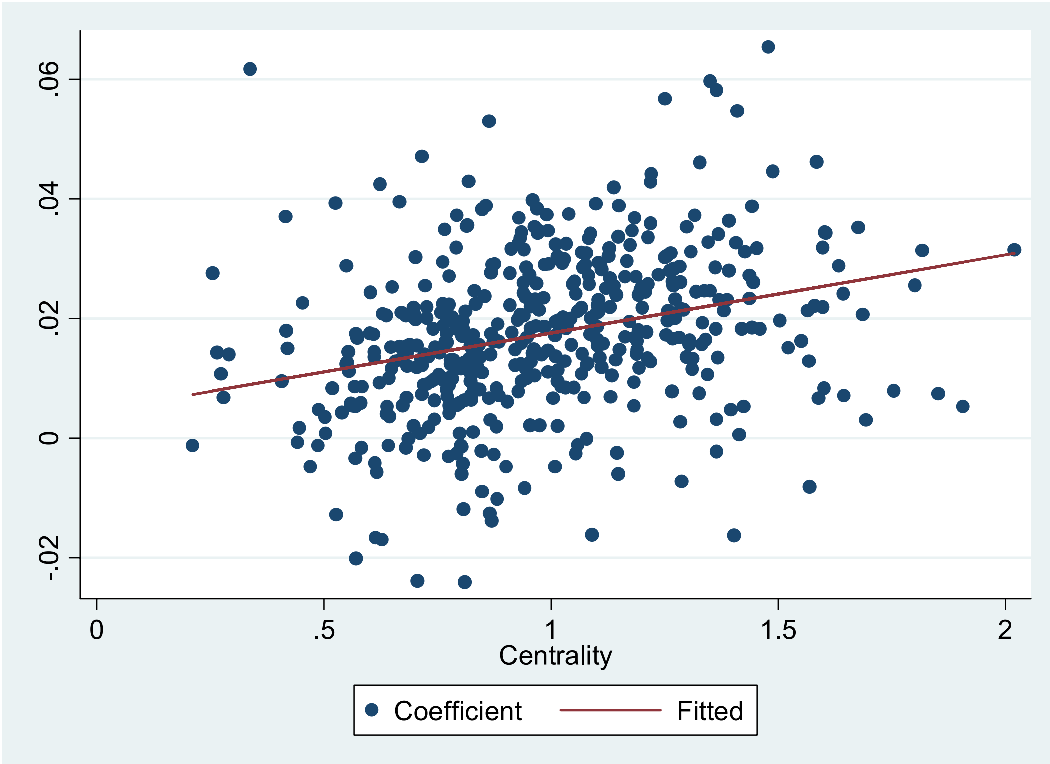
Figure 3



Title: City size premiums and centrality (log of employment)

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.

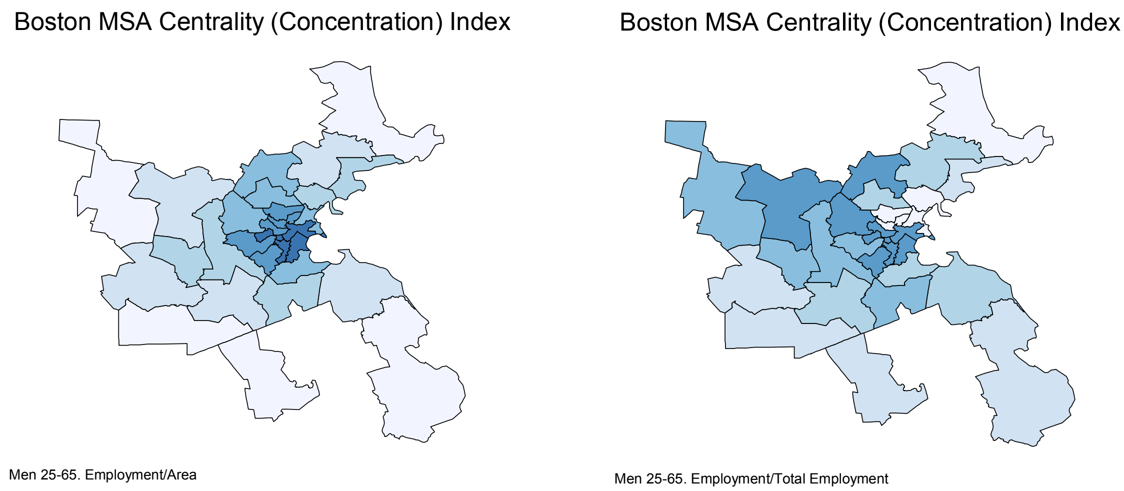
Figure 4



Title: City size premiums and centrality (commuting time)

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.

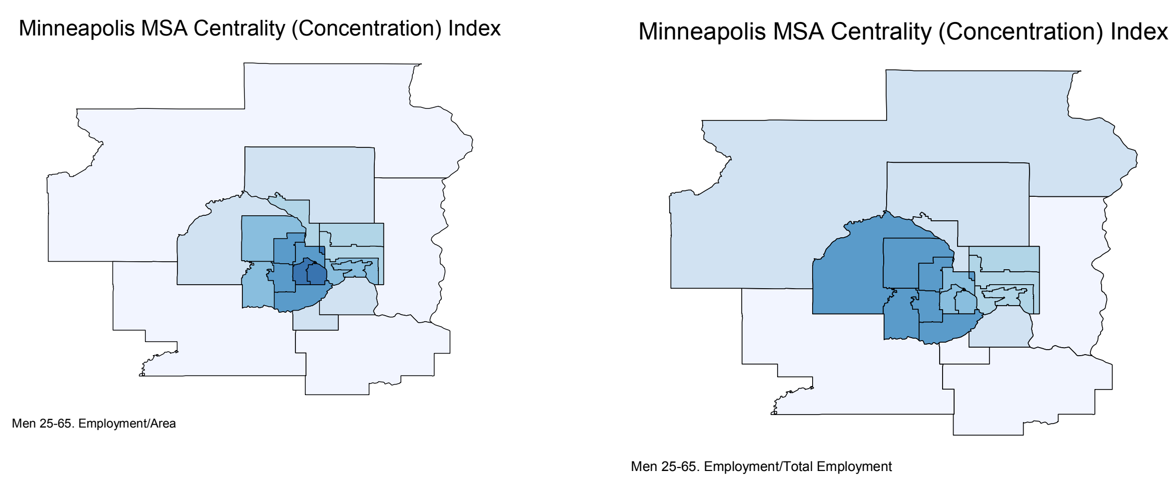
Figure 5



Title: Concentration indexes, Boston

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.

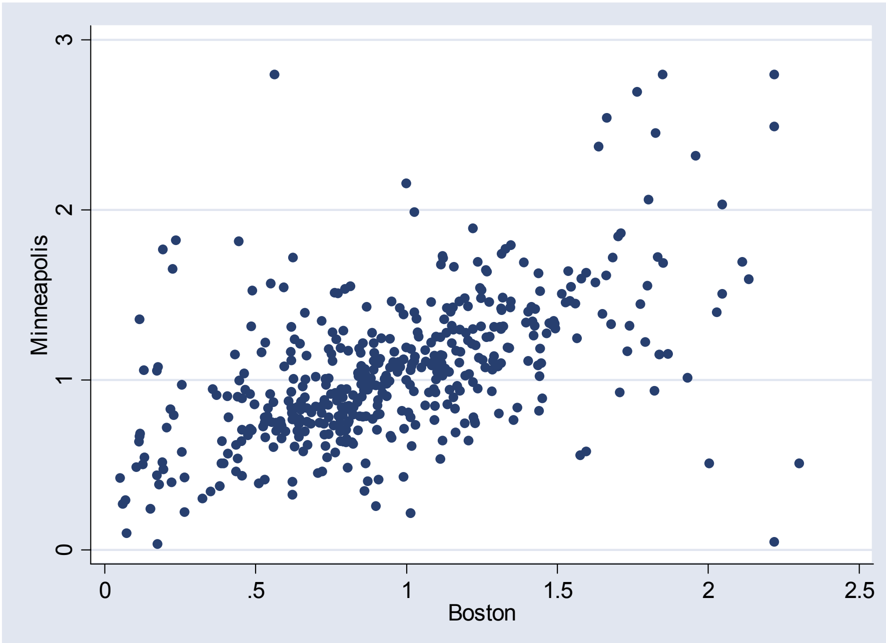
Figure 6



Title: Concentration indexes, Minneapolis

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.

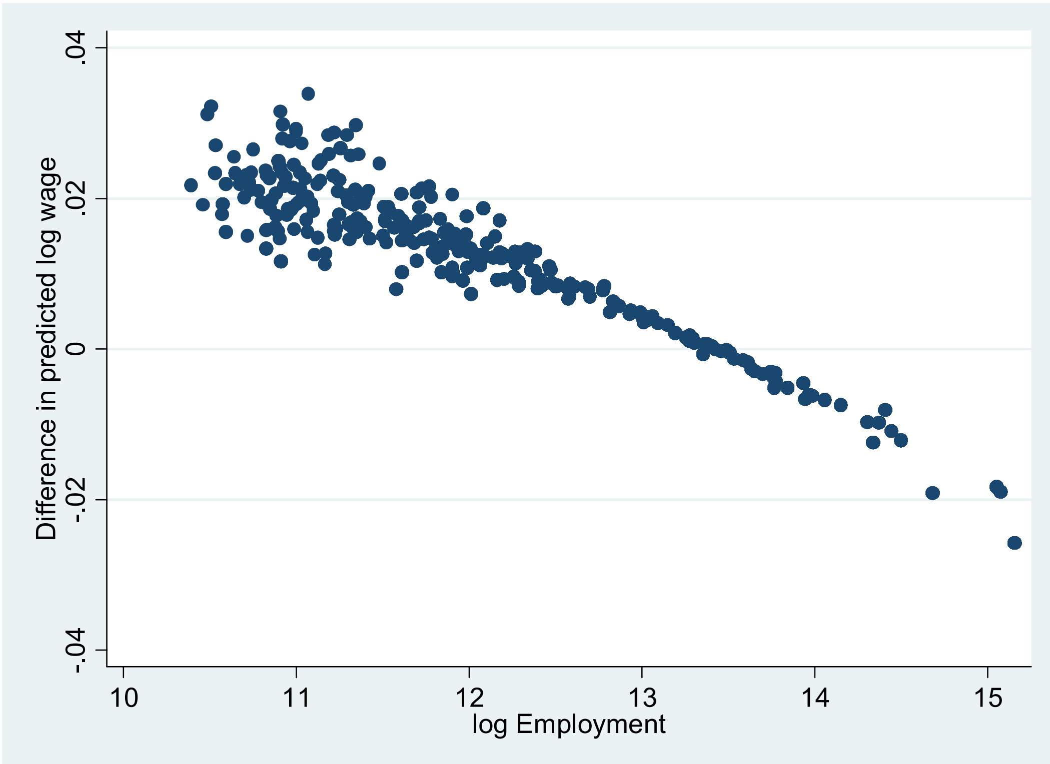
Figure 7



Title: Centrality indexes, Boston and Minneapolis

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.

Figure 8



Title: Predicted difference in teachers salary

Notes: Authors' calculations using 5% Sample of the US 2000 Census from the Integrated Public Use Microdata Series.