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What are Establishment Fixed Effects?

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Abstract

We use a largely untapped dataset, the BLS's Occupational Employment Statistics (OES) survey, to examine the nature of establishment fixed effects. We exploit the unique features of these data to define establishment fixed effects in a way that allows us to estimate the effects for a large number of establishments. We then examine how these effects vary by observed characteristics of establishments. These establishment-specific effects are estimated as average effects. But if they are unequally distributed within establishments, then it would be hard to argue that they are true establishment fixed effects. Therefore, we also we examine the extent to which these establishment-specific differentials are equally distributed.

We find the expected relationships between establishment fixed effects and observable characteristics of the establishment. However, we also find that establishments' wage policies tend to reduce inequality over what would be predicted by the mix of occupations employed by establishments.

I. Introduction

Economists have long recognized that wages vary across employers even after controlling for worker characteristics. This observation has always been somewhat of a puzzle because it seems to violate the law of one price—identical factors of production should be paid the same regardless of where they are employed. The availability of establishment and linked employer-employee microdata has sparked a renewed interest in this topic.

Several studies have examined the relative contributions of employer and individual effects in explaining the wage variation. The seminal article in this line of research, Groshen (1991), uses the Bureau of Labor Statistics' (BLS) Industry Wage Survey (IWS). The IWS collected data on wages by occupation for six manufacturing industries. Groshen found that employer effects explained a large fraction of wage variation, with about half of the employer effects being due to observable characteristics (such as size, industry, and location). Lane, Salmon, and Spletzer (2007) found similar results using the BLS's Occupational Employment Statistics (OES) data, which is similar to the IWS and covers service-providing industries as well as manufacturing. One drawback of the Groshen and Lane *et al.* studies is that their datasets do not include and demographic information on workers. However, Lane *et al.* examine the effect of not having this information and conclude that having employee information would not have materially changed their results.

Abowd *et al.* (1999) examine the relative importance of worker and firm effects using a unique French linked employer-employee dataset that includes demographic information on individuals, as well as information on firms. They find that employer effects are important, but that individual effects—including unobserved ability—account for most of the variation in wages.

One possible explanation for the differences in results is that the French labor market is very different from the U.S. market. Another has to do with how the different sets of authors treat occupation effects. Abowd *et al.* treat occupation as an individual effect (also, it is not clear how detailed their occupation codes are), while Groshen and Lane *et al.* interact occupation and establishment identifiers. However, given their inclusion of occupation-establishment interaction terms, it is not clear what is meant by an establishment fixed effect.

Our study departs from this literature in that our goal is not to determine the relative contribution of employer and employee effects to wage variation. Rather, our goal is to better understand what establishment fixed effects are by examining how differentials are distributed among the establishment's employees.[1]

We use the BLS's OES data to estimate establishment-occupation wage differentials, which are the differences between the prevailing market wages for an occupation in a labor market and the wage paid by the establishment for that occupation. We then aggregate these establishment-occupation wage differentials to calculate establishment-specific differentials.

Here and in the literature cited earlier, establishment fixed effects are estimated as average wage differentials. But if these differentials are concentrated in a few occupations, then it is hard to argue that they are true establishment fixed effects. Existing research (Lane et al. 2007) has shown that there is a positive within-establishment correlation between the wages of certain high-wage and low-wage pairs of occupations. For example, establishments that pay high wages to accountants also tend to pay high wages to janitors. Our procedure for estimating establishment-occupation wage differentials allows us to move away from pairwise comparisons and examine these relationships more generally.

[1] Our basic approach appears to be similar to that in a paper by Cardoso (1999). The focus of her study is on how changes establishments' wage-setting policies have affected overall earnings inequality. She models these wage-setting policies by allowing effects of individual characteristics to vary across establishments.

Our study contributes to the literature by delving into the nature of establishment fixed effects to an extent that has not been possible with existing U.S. linked employer-employee datasets.

II. Estimating Establishment-Occupation Wage Differentials

In this section we describe our method for estimating establishment-occupation wage differentials and aggregating them into establishment wage differentials. We begin by describing the underlying dataset that we use to estimate these differentials and then document our estimation method.

Data

We use data from the 2004 panels of the Occupational Employment Statistics (OES) survey conducted by the Bureau of Labor Statistics (BLS) to estimate establishment-occupation wage differentials. The OES survey is a semi-annual mail survey that samples approximately 200,000 establishments in May and November of each year. The survey covers all workers, both full time and part time, in private non-agricultural industries. We further restricted our sample to non-governmental establishments.

The survey instrument asks establishments to provide what amounts to a complete payroll record for the pay period that includes the 12th of the sample month. Due to the fact that the OES is designed as a mail survey, respondents report occupational wage information using wage intervals.[2] The form contains a list of occupations (with accompanying wage intervals). For each occupation in the establishment, the respondent reports the number of workers in each

[2] Wages for the OES survey represent straight-time, gross pay, exclusive of premium pay. Base rate, cost-of-living allowances, guaranteed pay, hazardous-duty pay, incentive pay including commissions and production bonuses, tips, and on-call pay are included while back pay, jury duty pay, overtime pay, severance pay, shift differentials, non-production bonuses, employer cost for supplementary benefits, and tuition reimbursements are excluded from the reported wage.

occupation who earn an hourly (or corresponding annual) wage in each of the 12 pre-defined wage intervals, with the top interval being open-ended. The example below shows the information that would be collected for a single establishment-occupation observation. The hypothetical establishment employs 100 workers in this occupation. Of these 100 workers, 10 workers earn between $6.75 and $8.49, 25 earn between $8.50 and $10.74, 25 earn between $10.75 and $13.49, and 40 earn between $13.50 and $16.99.

An Example of an OES establishment-occupation observation

Wage Interval	Interval Bounds	Number of Workers
A	Under $6.75	0
B	$6.75 to $8.49	10
C	$8.50 to $10.74	25
D	$10.75 to $13.49	25
E	$13.50 to $16.99	40
F	$17.00 to $21.49	0
G	$21.50 to $27.24	0
H	$27.25 to $34.49	0
I	$34.50 to $43.74	0
J	$43.75 to $55.49	0
K	$55.50 to $69.99	0
L	$70.00 and above	0
T	All Workers	100

This information is collected for each occupation in the establishment. The OES survey uses the Office of Management and Budget's (OMB) occupational classification system, the Standard Occupational Classification (SOC), to categorize workers into 801 detailed occupations. The SOC system is much richer and provides much more occupational detail than most other surveys that include information about occupation.

Total employment in an establishment is derived by aggregating employment over wage intervals for each occupation and then aggregating over occupations. For notational purposes, let n_{jeb} denote the number of workers in establishment *e* in occupation *j* who earn an hourly wage in wage interval *b*. Therefore, employment in establishment *e* in occupation *j* is given by

$$n_{je} = \sum_{b=A}^{L} n_{jeb} \tag{1}$$

and the size of establishment *e* is

$$n_e = \sum_{j=1}^{J_e} n_{je} = \sum_{j=1}^{J_e} \sum_{b=A}^{L} n_{jeb} \tag{2}$$

where J_e represents the number of occupations that establishment *e* employs.

As will be clear below, our empirical analysis relies in large part on the definition of local labor markets. To this end, we define a local labor market as an occupation and area pair, *(j,a)*. Our dataset includes 157,749 labor markets, but a large majority of those markets are small in the sense that the labor market either has only a few employers (less than 5), has few workers (less than 50), or has one dominant employer that accounts for more than 50% of employment in the market. Once we have eliminated these small markets we are left with 26,285 markets to consider.

We restricted our sample to include only those establishments located in metropolitan areas who operate in the private sector and who actually supply wage data to the OES program.[3] After imposing these restrictions our sample includes 219,399 establishments located in 375 metropolitan areas that employ a total of 11,999,731 workers in 787 different occupations.

[3] Since we are seeking to estimate establishment-occupation wage differentials we have excluded imputed data from our analysis. In the current version we have not adjusted the establishment weights to account for this exclusion, but plan to do so in the future.

Estimation Method

We seek to estimate establishment-occupation wage differentials and establishment fixed effects (average wage differentials). Specifically, we estimate the difference between what a particular employer pays a specific occupation (on average) and the prevailing market wage (the wage for the occupation-area cell)

$$d_{je_a} = \overline{w}_{je_a} - \overline{w}_{ja} \tag{3}$$

where $\overline{w}_{je_a}$ represents the average wage paid to a worker in occupation *j* at establishment e_a and $\overline{w}_{ja}$ is the prevailing wage in the *(j,a)* labor market. The subscript *a* indicates that the establishment operates in area *a*.

If we had access to each employee's wages, the estimation of the establishment-occupation wage differentials would be straightforward. However, the fact that OES wage data is collected in intervals complicates the matter slightly. One obvious approach is to assign a single value to each wage interval and then compute the weighted (by the number of workers in each interval) average for the establishment-occupation pair and the labor market.[4]

Following this approach, if we assume that all workers in the *(j,a)* labor market who are paid an hourly wage in interval *b* earn a wage of $\hat{w}_{jab}$, it follows that the average wage of workers in occupation *j* at establishment e_a is

$$\overline{w}_{je_a} = \frac{1}{n_{je_a}} \sum_{b=A}^{L} n_{je_a b} \times \hat{w}_{jab} \,. \tag{4}$$

[4] In fact this is exactly the approach that the OES program currently employs. They estimate the mean wage for each interval using a secondary data source and assume (for calculation of mean wages) that every wage that is reported in this interval equals the estimated wage. With the exception of statewide variation in minimum wages that affect the interval means for the bottom two intervals, there is no variation in the values that are used to compute occupational mean wages by area.

Letting E_{ja} represent the number of establishments in the *(j,a)* labor market, the number of workers in the market who earn an hourly wage in interval *b* is given by

$$n_{jab} = \sum_{e_a=1}^{E_{ja}} n_{je_a b} \tag{5}$$

and the total number of workers in the market is simply

$$n_{ja} = \sum_{b=A}^{L} n_{jab} \ . \tag{6}$$

Then, the prevailing wage in the market is given by

$$\overline{w}_{ja} = \frac{1}{n_{ja}} \sum_{b=A}^{L} n_{jab} \times \hat{w}_{jab} \ . \tag{7}$$

We now turn to the computation of the interval wage values, $\{\hat{w}_{jab}\}_{b=A}^{L}$.

The collection of wage information through the use of wage intervals naturally leads to the use of a maximum likelihood estimator. The first step in the definition of this estimator is to make a parametric assumption regarding the shape of the wage distribution in the local labor market, *(j,a)*. To that end, we assume that

$$\ln w_{ja} \sim N\left(\mu_{ja}, \sigma_{ja}^2\right)$$

so that wages in the local labor market follow a lognormal distribution.

Assuming a constant (i.e., does not vary by area) minimum wage, the log-normality assumption implies that the probability that the hourly wage in the *(j,a)* labor market falls into interval *b* is

$$\Pr\left(w_{ja} \in b\right) = \frac{\Phi\left(\frac{\ln w_b^u - \mu_{ja}}{\sigma_{ja}}\right) - \Phi\left(\frac{\ln w_b^l - \mu_{ja}}{\sigma_{ja}}\right)}{1 - \Phi\left(\frac{\ln w_{\min} - \mu_{ja}}{\sigma_{ja}}\right)} \tag{8}$$

where w_b^u is the upper bound of wage interval *b*, w_b^l is the lower bound of wage interval *b*, $w_{\min}$ represents the federal minimum wage, and Φ denotes the standard normal CDF.

With the underlying frequency distribution observed in the OES data, we then define the log-likelihood function by

$$\ln L\left(\{n_{jab}\}_{b=A}^{L}; \mu_{ja}, \sigma_{ja}\right) = \sum_{b=A}^{L} n_{jab} \times \ln \Pr\left(w_{ja} \in b\right). \tag{9}$$

It is straightforward to maximize (9) with respect to the parameters, μ_{ja} and σ_{ja}^2. With the maximum likelihood estimates in hand, we can easily compute the interval mean wages for the *(j,a)* labor market and assign that wage to each individual who earns a wage in the interval. In particular, we estimate the interval wage values according to

$$\hat{w}_{jab} = \overline{w}_{jab} = \frac{\displaystyle\int_{w_b^l}^{w_b^u} \phi\left(\frac{\ln w - \mu_{ja}}{\sigma_{ja}}\right) dw}{\displaystyle\int_{w_b^l}^{w_b^u} w^{-1} \phi\left(\frac{\ln w - \mu_{ja}}{\sigma_{ja}}\right) dw} \tag{10}$$

where ϕ is the standard normal PDF.

Finally, in the results that we present and discuss below, an establishment-occupation wage differential is estimated as the percent difference between the wage an establishment pays its workers in an occupation and the prevailing wage in the local labor market or

$$\theta_{je} = \frac{\overline{w}_{je} - \overline{w}_{ja}}{\overline{w}_{ja}}. \tag{11}$$

The overall establishment fixed effect or, more precisely, the weighted average of the establishment-occupation percent wage differentials,

$$\theta_e = \frac{1}{n_e} \sum_{j=1}^{J_e} \theta_{je} \times n_{je} \tag{12}$$

Another way to think of the establishment fixed effect is that it is the difference between the average wage paid by the establishment and the average wage that the establishment would have paid if it paid the area-specific average wage for each occupation that it employs (employment weighted), which we refer to as the counterfactual wage and is given by:

$$\widetilde{\theta}_e = \frac{\sum_{j \in J^e} \left(\overline{w}_{ja} \times n_{ja}^e \right)}{\sum_{j \in J^e} n_{ja}^e}.$$

Note also that, by construction, the employment-weighted sum of establishment fixed effects equals zero.

III. Results

In this section, we present results from four major metropolitan areas: New York, Los Angeles, Chicago, and Dallas. We chose these areas because they are large and are geographically diverse. In the next draft of this paper, we will include more metropolitan areas and combine them to see if our findings hold in the aggregate.

We first examine how establishment fixed effects vary with several establishment characteristics. Then, we examine how these fixed effects are distributed across occupations within the establishment.

Establishment Fixed Effects

Figures 1-4 show the distribution of establishment fixed effects, and how these fixed effects vary across industries, by establishment size, and by the average counterfactual wage. Each figure has four panels corresponding to the four MSAs. Distributions and fitted lines are employment weighted.[5] Figure 1 shows the distribution of establishment fixed effects. The distributions look fairly similar in each of the MSAs. The distributions are approximately symmetric and centered around zero.

Figure 2 shows box-and-whisker plots of establishment fixed effects by industry. The left and right edges of each box show the 25th and 75th percentiles, while the line in the middle of the box represents the median. Industries are sorted by median establishment fixed effects from largest to smallest. It is clear from the plots that median fixed effects vary by industry within each MSA. Comparing panels, we can see that the ordering of industries varies across MSAs and that only a few industries are consistently ranked from MSA to MSA. For example, Retail Trade and Other Services generally rank at or near the bottom with relatively large negative median fixed effects. In contrast Leisure & Hospitality, which is generally considered a low-paying industry, has negative median establishment fixed effects in most MSAs, but does not rank at the bottom in any MSA. Manufacturing, which is generally considered high paying, has the highest median fixed effect only in Dallas. In New York, the median establishment fixed effect in Manufacturing is negative and has the third lowest median fixed effect. It is worth keeping in mind that a large positive establishment fixed effect does not necessarily imply that average wages in the establishment are high—only that the establishment on average pays more than the going wage for the occupations that it employs. The average wage in the establishment could still be low if the establishment employs low-paying occupations.

Figure 3 shows how establishment fixed effects vary by establishment size. To make the graph more readable, we logged employment. Because it is difficult to discern trends from the scatter plots, we have added lines showing predicted establishment fixed effects based on fractional polynomial regressions. These graphs are generally consistent with the findings of

[5] Weights were generated by multiplying each establishment's sample weight by its employment.

Brown and Medoff (1989) and others who have found that wages increase with establishment size. The fitted values indicate that establishment fixed effects increase with establishment size in the Dallas, Los Angeles, and New York MSAs.

To better see the magnitude of the differences by establishment size, we present means by establishment size category in Table 1. The difference in average fixed effect between the largest and smallest establishments range from 0.036 in Chicago to 0.14 in Dallas, and is about 0.1 in Los Angeles and New York. Thus, larger establishment pay wages that are 4−14 percent higher than the wages that would be predicted based on their occupation mix.

Figure 4 shows the relationship between the counterfactual average wage, which we will view as a measure of skill intensity, and the establishment fixed effect. Here, we see that firms that are more skill-intensive—employ high-wage occupations—tend to have larger fixed effects. Comparing the highest-paying and lowest-paying establishments in each of the MSAs in Table 2, we see that the average establishment fixed effect is about 10−15 percentage points higher in the more skill-intensive establishments.

What we have learned from Figures 1-4 is that the distribution of establishment fixed effects is fairly symmetric and generally not skewed; that there is a lot of variation in establishment fixed effects by industry, although the ranking of industries by fixed effects varies by MSA; and that establishment fixed effects increase with establishment size and with the average skill level as measured by the average wages of the occupations employed by the establishment.

Establishment-Occupation Wage Differentials

Next, we would like to examine how establishment-occupation wage differentials are distributed across occupations within an establishment—especially how they are distributed between high and low paying occupations. We depart from the Lane et al. (2007) analysis in that we do not make pairwise comparisons of occupations. Instead, we compare the occupation-specific fixed effect for the top and bottom quarter of employees in each establishment, where the top and bottom quarters are determined by the average wage paid in the MSA for that occupation.[6] The top and bottom quarters could be composed of several occupations or just one. However, for this analysis, we restricted our sample to establishments with at least 20 employees so that the average establishment-occupation wage differential for each quarter is based on at least 5 employees. The main advantages of this approach are that we are not restricted to establishments that have a certain set of occupations, and small occupations will not disproportionately affect results.

Figure 5 shows scatter plots of the average establishment-occupation wage differentials for the top and bottom quarters of employees in each establishment. In this and the following figures, we dropped the small number of establishment that had differences greater than one in absolute value. We can see that there is a positive relationship indicating that establishments that pay positive wage differential to workers in high-paying occupations also pay positive wage differentials to worker in low-paying occupations. The correlation between the wage differential of the top and bottom quarter in the four MSAs ranges between 0.46 and 0.49. The slope of the fitted line is less than one, indicating that increases in the establishment-occupation wage differentials for the bottom quarter are smaller than increases for the top quarter. However, it is important to note that most of the mass lies above the 45-degree line in the region where the

[6] We considered two other measures. The first is a regression coefficient. For each establishment, we regressed the establishment-occupation wage differential on the average wage for that occupation (expressed as a deviation from the counterfactual average wage for the establishment). The coefficient shows the relationship between the skill level of the occupation (as measured by the average wage for that market) and the establishment-occupation wage differential. The second is based on the Gini coefficient. For each establishment, we computed the Gini coefficient using the average market wage for each occupation and again using the actual wage. The difference between the two Gini coefficients measures the extent to which the establishment's wage-setting practices increase or decrease within-establishment inequality. Both of these measures tell the same qualitative story as the top-bottom difference.

average wage differential is larger for the bottom quarter than for the top quarter. On a weighted basis, two-thirds of establishments (representing about 70 percent of employment) pay larger differentials to their lower-paying occupations. Figure 6, which shows the density of the difference in average wage differentials between the top and bottom quarters, confirms this pattern. A negative difference indicates that the mean establishment-occupation wage differential for the bottom quarter of employees is greater than the wage differential for the top quarter. We can easily see from Figure 6 that the differences are mostly negative.

Figures 7-9 show how the top-bottom differences vary by industry, establishment size, skill intensity. In Figure 7, we can see that the median difference is negative for all industries in the four MSAs. Industries are sorted by median top-bottom difference from smallest (most equal) to largest (least equal). We can see that Leisure & Hospitality has relatively large differences in three of the four MSAs indicating that wage policies in this industry tend to increase within-establishment inequality. The differences in Business & Professional services also tend to be large. But as in Figure 2, the other industries show no clear pattern across MSAs.

Figure 8 and Table 3 reveal no consistent pattern across MSAs with respect to establishment size. The top-bottom differences appear to decline with establishment size in Chicago and Los Angeles, and for most of the range in New York, and remain constant for most of the range in Dallas. But in Table 3, which shows the mean top-bottom difference in the wage differential by establishment size category, the pattern is less clear. The overall mean differences to not vary much by MSA, ranging from −0.15 to −0.10. The magnitude of the mean differences are largest for for the largest establishments, but the relationship is not monotonic within MSA. For example, in the Chicago MSA, the fitted line in Figure 8 shows a noticeable decline with establishment size, but this pattern does not show up in Table 3.

Figure 9 shows the top-bottom difference by skill intensity as measured by the counterfactual wage. Again the fitted lines show no clear pattern across the four MSAs. The difference declines with skill intensity in Chicago and Los Angeles, and remain approximately constant in Dallas and New York. It is a little easier to see the patterns in Table 4. The top-bottom difference declines with skill intensity in all for MSAs, but the decline is not monotonic. In all four MSAs, the lowest-skilled establishments tend to have smaller differences, while, except for Chicago, medium-to-high-skilled establishments do not have the largest differences.

IV. Preliminary Conclusions and Future Work

We used data from the BLS's OES survey to examine establishment fixed effects and found that, consistent with earlier research, these effects vary with observable establishment characteristics. Looking within establishments, we find a positive correlation between high- and low-paying occupations. Thus, the wage-setting policies in most establishments tend to reduce within-establishment inequality by paying greater establishment-occupation wage differentials to lower-paying occupations. Somewhat surprisingly, we found that the top-bottom differences in establishment-occupation wage differentials did not vary systematically with establishments' size or average skill level.

Our procedure for computing occupation-by-establishment wage differentials for the large number of establishments in the OES opens the door for more analyses of this type. Previous studies relied on industry and occupational dummies to estimate these effects, which limited the number of establishments that could be considered. Our procedure removes these limitations.

The equalizing effects of establishments' wage setting policies are consistent with fair-wage models as described in Thayler (1989). In the next draft of this paper, we intend to examine whether the observed patterns are consistent with other economic models of within-firm behavior. To this end, we plan on extending our work to learn more about the nature of establishment fixed effects. If we view the different occupational distributions as different production functions, we would expect to see establishment-specific wage differentials to vary systematically with the occupational distribution. We can also see if establishment fixed effects are persistent over time.

References

Abowd, John M., Francis Kramarz, and David N. Margolis (1999) "High Wage Workers and High Wage Firms." *Econometrica* 67(2), March, pp. 251-333.

Brown, Charles and James Medoff (1989) "The Employer Size-Wage Effect." *Journal of Political Economy* 97(5), October, pp.1027-1059.

Cardoso, Ana Rute (1999) "Firm's Wage Policies and the Rise in Labor Market Inequality: The Case of Portugal." *Industrial and Labor Relations Review* 53(1), October, pp. 87-102.

Groshen, Erica L. (1991) "Sources of Intra-Industry Wage Dispersion: How Much Do Employers Matter?" *Quarterly Journal of Economics* 106(3), August, pp. 869-884.

Lane, Julie I., Laurie A. Salmon, and James R. Spletzer (2007) "Establishment Wage Differentials." *Monthly Labor Review* 130(4), April, pp. 3-17.

Thayler, Richard (1989) "Anomalies: Interindustry Wage Differentials." *Journal of Economic Perspectives* 3(2), Spring, pp. 181-193.

Figure 1

Weighted Distribution of Establishment Fixed Effects

Graphs by Metropolitan Area

Figure 2

Establishment Fixed Effects by Supersector

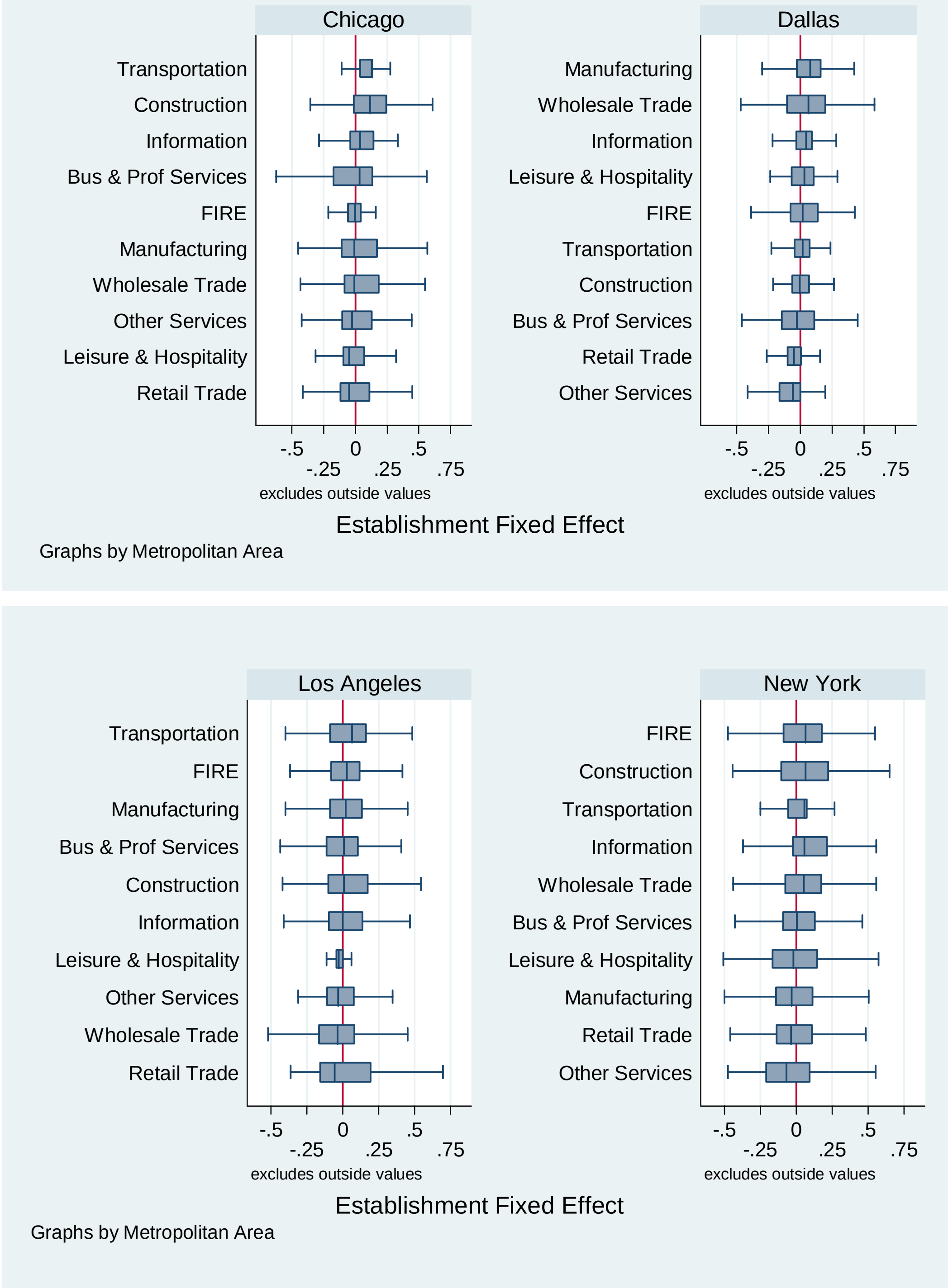
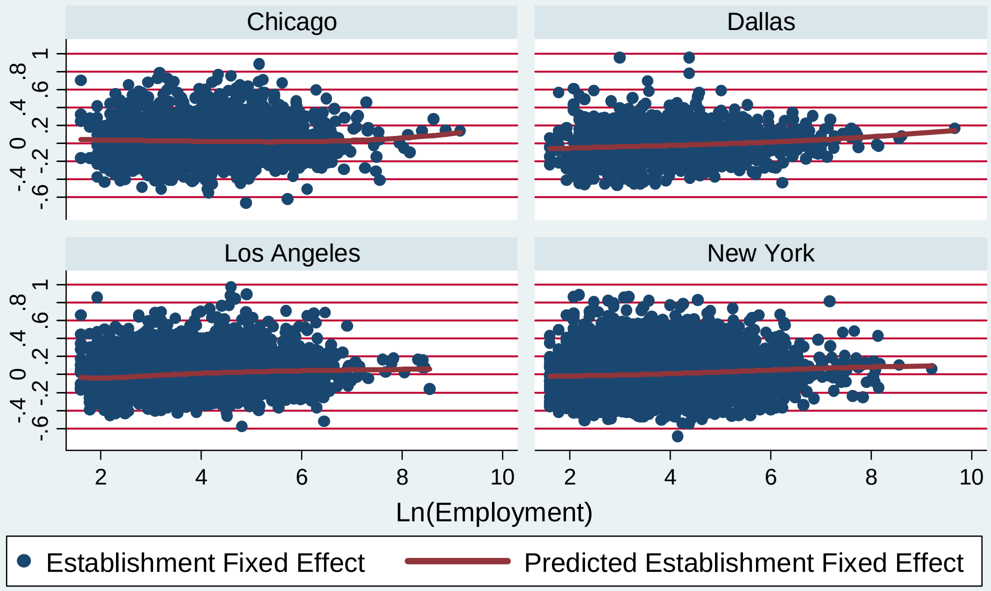


Figure 3

Establishment Fixed Effects by Establishment Size



Graphs by Metropolitan Area

Table 1
Mean Establishment Fixed Effect by Establishment Size

	MSA [Number of establishments is in brackets]			
	Chicago	Dallas	Los Angeles	New York
Number of Employees				
<20	0.027	-0.060	-0.032	-0.006
	[302]	[286]	[512]	[1268]
20-49	-0.002	-0.027	-0.001	0.005
	[496]	[369]	[822]	[1588]
50-99	0.038	0.001	0.046	0.020
	[442]	[285]	[720]	[1035]
100-499	0.033	-0.008	0.020	0.021
	[614]	[362]	[899]	[1076]
500-999	0.012	0.056	0.057	0.083
	[61]	[50]	[75]	[71]
1000+	0.063	0.080	0.067	0.089
	[23]	[27]	[21]	[44]
All Establishments	0.030	0.014	0.021	0.027
	[1938]	[1379]	[3049]	[5082]

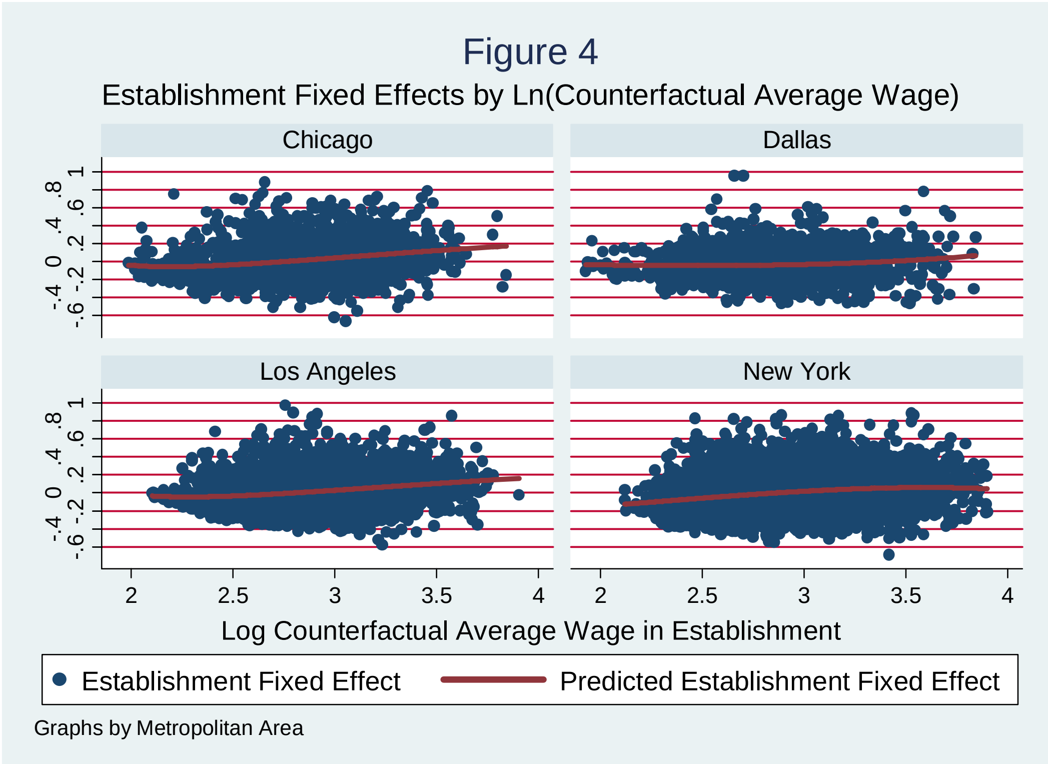


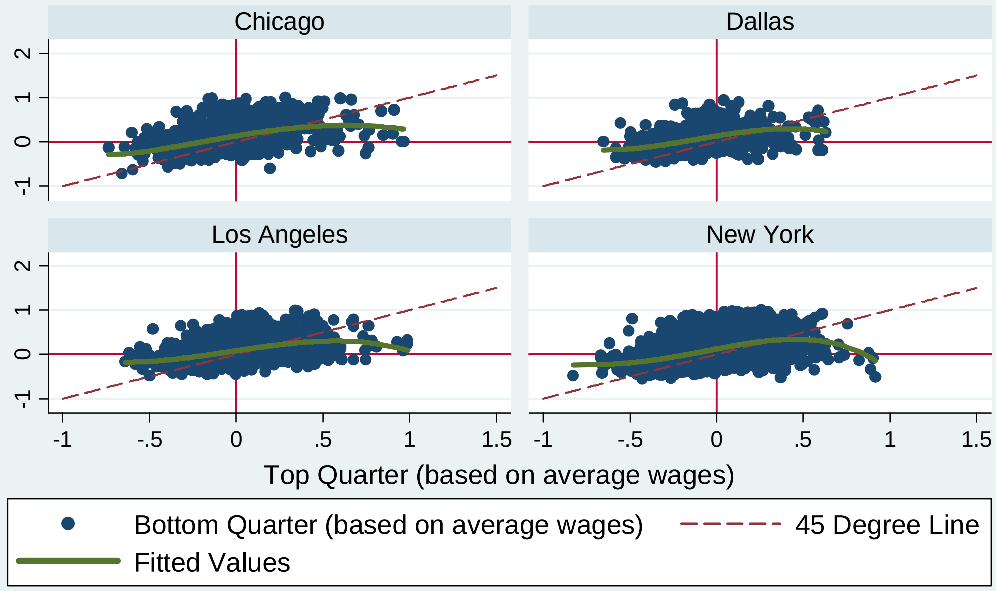
Figure 4
Establishment Fixed Effects by Ln(Counterfactual Average Wage)
Chicago
Dallas
Los Angeles
New York
-.6 -.4 -.2 0 .2 .4 .6 .8 1
2 2.5 3 3.5 4
Log Counterfactual Average Wage in Establishment
Establishment Fixed Effect
Predicted Establishment Fixed Effect
Graphs by Metropolitan Area

Table 2
Mean Establishment Fixed Effect by Counterfactual Average Wage

	MSA [Number of establishments is in brackets]			
	Chicago	**Dallas**	**Los Angeles**	**New York**
Counterfactual Average Wage Range				
<10	-0.015	-0.006	-0.026	-0.050
	[92]	[56]	[96]	[48]
10-14.99	-0.031	-0.043	-0.028	-0.020
	[538]	[419]	[876]	[1166]
15-19.99	0.041	-0.008	0.045	0.005
	[655]	[433]	[997]	[1351]
20-24.99	0.098	0.014	0.040	0.043
	[384]	[221]	[581]	[1151]
25-29.99	0.100	0.074	0.051	0.079
	[182]	[138]	[295]	[689]
30+	0.079	0.094	0.124	0.076
	[87]	[112]	[204]	[677]
All Establishments	0.030	0.014	0.021	0.027
	[1938]	[1379]	[3049]	[5082]

Figure 5

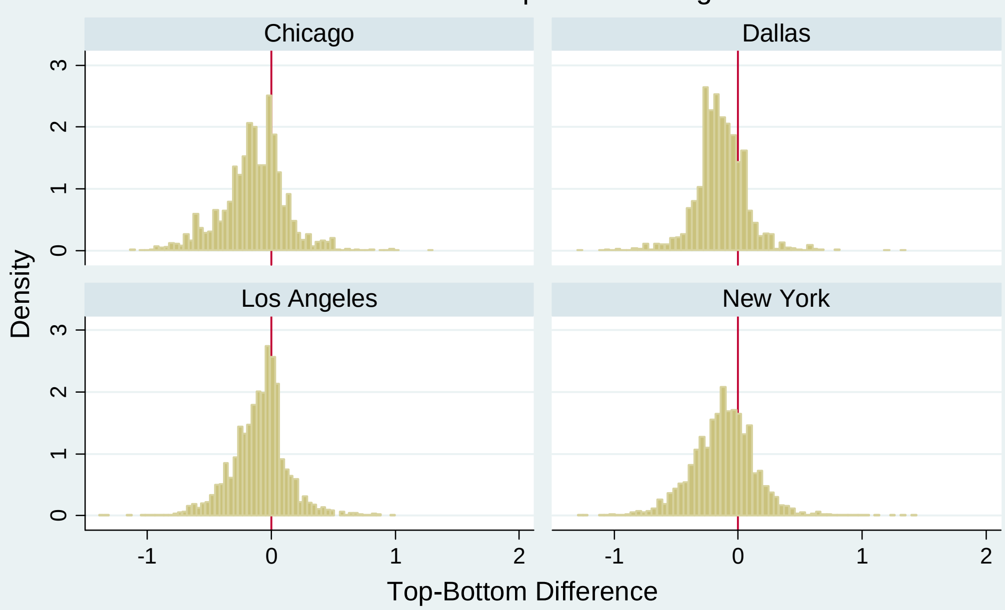
Mean Est.-Occ. Wage Differentials - Top and Bottom Quarters



Graphs by Metropolitan Area

Figure 6

Distribution of Difference in Top-Bottom Wage Differentials



Graphs by Metropolitan Area

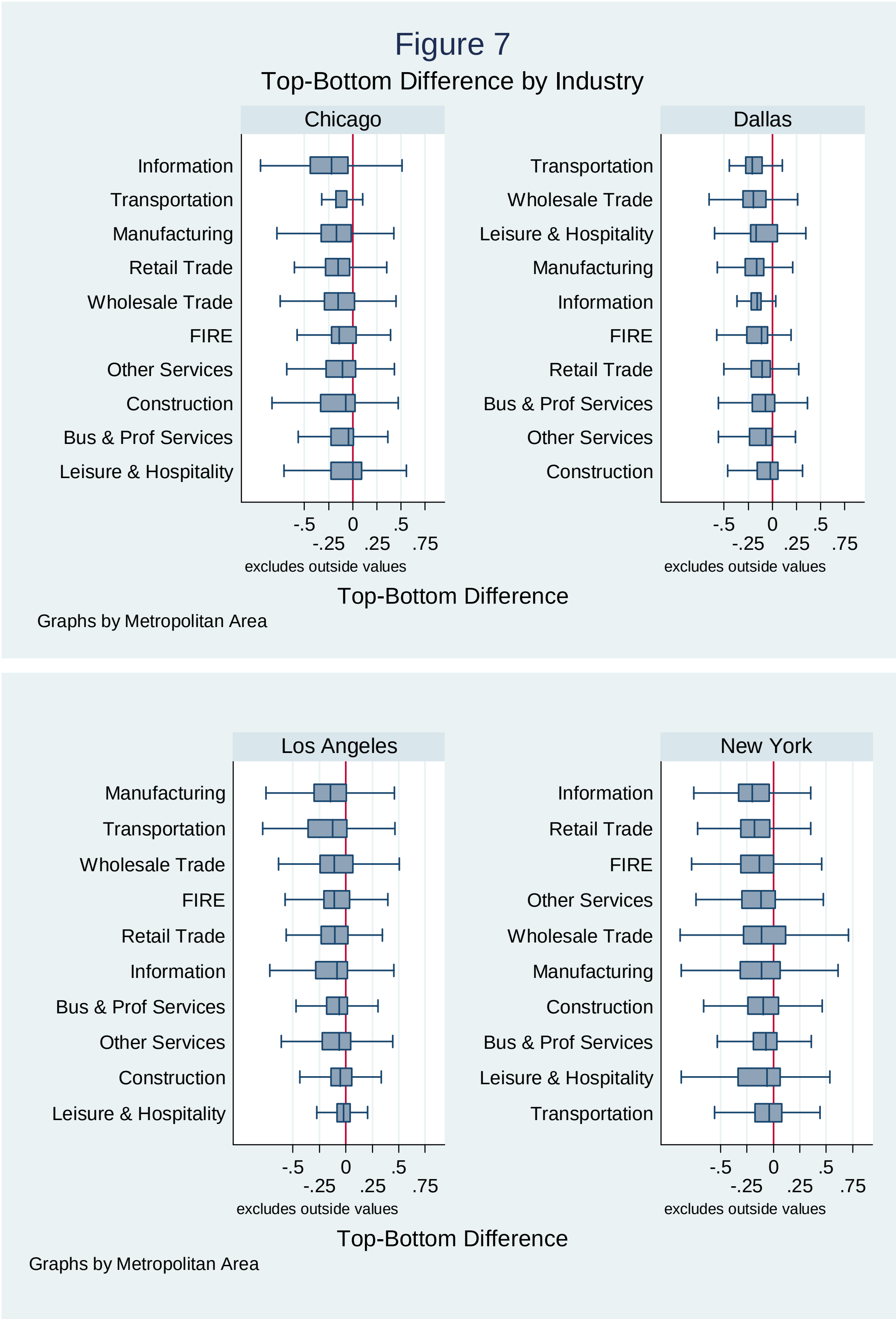
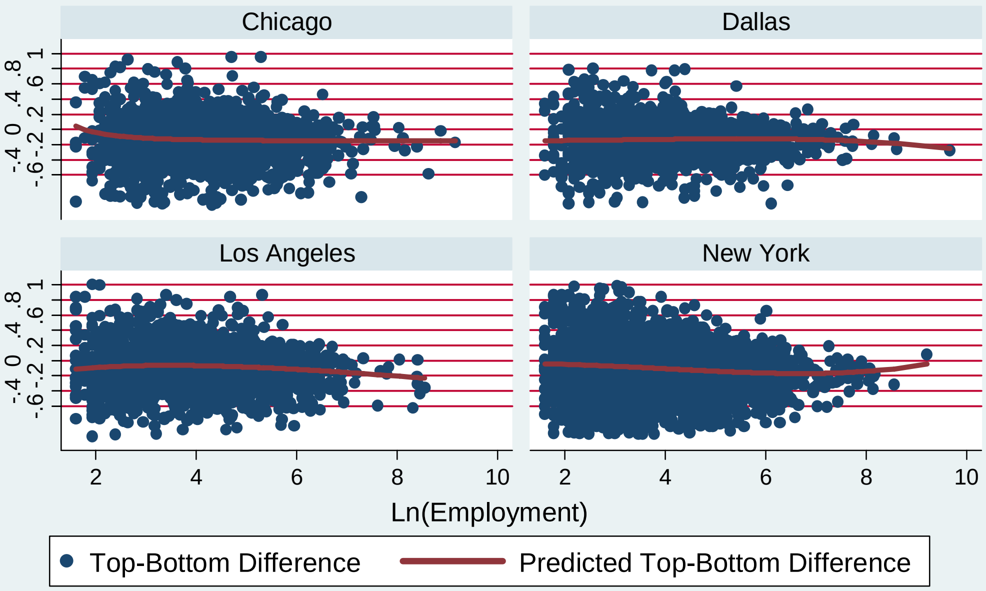


Figure 7
Top-Bottom Difference by Industry
Chicago
Information
Transportation
Manufacturing
Retail Trade
Wholesale Trade
FIRE
Other Services
Construction
Bus & Prof Services
Leisure & Hospitality
-.5 0 .5
-.25 .25 .75
excludes outside values
Dallas
Transportation
Wholesale Trade
Leisure & Hospitality
Manufacturing
Information
FIRE
Retail Trade
Bus & Prof Services
Other Services
Construction
-.5 0 .5
-.25 .25 .75
excludes outside values
Top-Bottom Difference
Graphs by Metropolitan Area
Los Angeles
Manufacturing
Transportation
Wholesale Trade
FIRE
Retail Trade
Information
Bus & Prof Services
Other Services
Construction
Leisure & Hospitality
-.5 0 .5
-.25 .25 .75
excludes outside values
New York
Information
Retail Trade
FIRE
Other Services
Wholesale Trade
Manufacturing
Construction
Bus & Prof Services
Leisure & Hospitality
Transportation
-.5 0 .5
-.25 .25 .75
excludes outside values
Top-Bottom Difference
Graphs by Metropolitan Area

Figure 8

Top-Bottom Difference by Ln(Establishment Size)



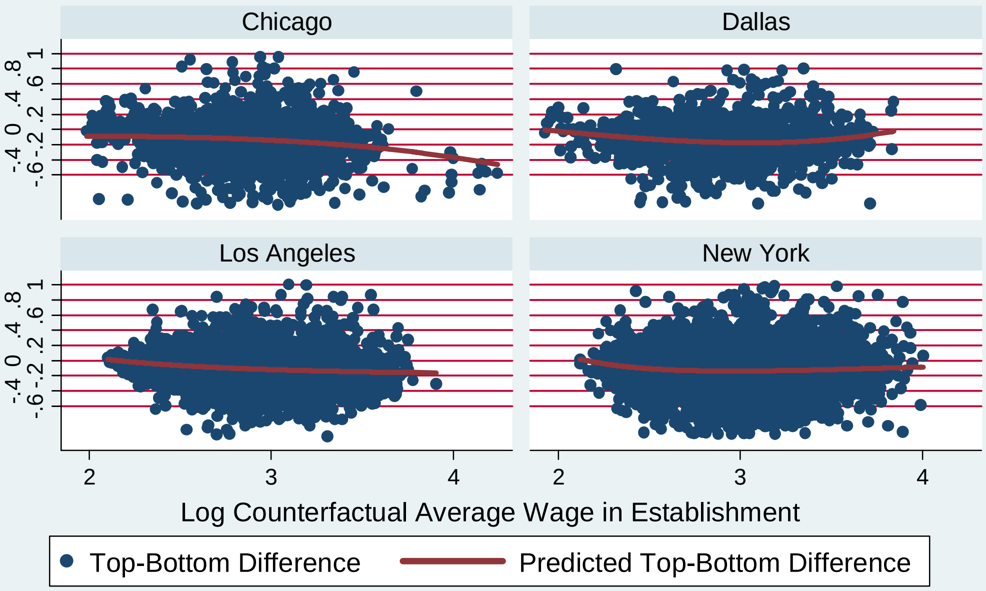
Graphs by Metropolitan Area

Table 3
Mean Top-Bottom Difference in Wage Differential by Est. Size

	MSA [Number of establishments is in brackets]			
	Chicago	**Dallas**	**Los Angeles**	**New York**
Number of Employees				
<20	-0.150	-0.138	-0.113	-0.100
	[302]	[286]	[512]	[1268]
20-49	-0.115	-0.126	-0.049	-0.102
	[496]	[369]	[822]	[1588]
50-99	-0.139	-0.127	-0.084	-0.093
	[442]	[285]	[720]	[1035]
100-499	-0.155	-0.154	-0.094	-0.136
	[614]	[362]	[899]	[1076]
500-999	-0.164	-0.099	-0.155	-0.194
	[61]	[50]	[75]	[71]
1000+	-0.155	-0.171	-0.182	-0.157
	[23]	[27]	[21]	[44]
All Establishments	-0.146	-0.143	-0.095	-0.124
	[1938]	[1379]	[3049]	[5082]

Figure 9

Top-Bottom Difference by Ln(Counterfactual Average Wage)



Graphs by Metropolitan Area

Table 4
Mean Top-Bottom Difference in Wage Differential by Counterfactual Average Wage

	MSA [Number of establishments is in brackets]			
	Chicago	**Dallas**	**Los Angeles**	**New York**
Counterfactual Average Wage Range				
<10	-0.077	-0.066	-0.012	-0.035
	[92]	[56]	[96]	[48]
10-14.99	-0.119	-0.128	-0.069	-0.115
	[538]	[419]	[876]	[1166]
15-19.99	-0.156	-0.162	-0.106	-0.128
	[655]	[433]	[997]	[1351]
20-24.99	-0.191	-0.153	-0.144	-0.155
	[384]	[221]	[581]	[1151]
25-29.99	-0.131	-0.182	-0.111	-0.138
	[182]	[138]	[295]	[689]
30+	-0.228	-0.122	-0.161	-0.111
	[87]	[112]	[204]	[677]
All Establishments	-0.146	-0.143	-0.095	-0.124
	[1938]	[1379]	[3049]	[5082]