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Megafirms and Monopsonists: Not the same employers, not the same workers

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Abstract: There has been an explosion of interest in the role of very large employers and in employers with monopsony power in local labor markets. We use the detailed microdata of the Occupational Employment Statistics (OES) to show that these are not the same. We construct measures of megafirm employment and employer labor market power, following multiple approaches found in this growing literature, for nearly all workers in the United States, in all sectors, all occupations, and all geographic areas, from 2005 to 2017. We show there is no correlation between the extent of employment in megafirms for a geographic area and that area's average level of employer concentration across occupations or across industries, but extremely high correlation between average levels of employer concentration across occupations and employer concentration across industries for geographic areas. We show that employer concentration is generally falling with employment size in geographic areas or occupations, but there is no such relationship between employment size in areas or occupations and the share of employment in megafirms. Furthermore, trends in employment in megafirms are very different from trends in highly concentrated labor markets.

We also show that relatively few of the employees of megafirms are employed by local oligopsonists, and relatively few of the employees of local oligopsonists are employed in megafirms. Those employed by both megafirms and oligopsonists are disproportionately found in the public sector.

Disclaimer: Any opinions and conclusions herein are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics.

Introduction

An enormous literature, dating back decades, shows a pervasive wage gap between larger and smaller employers, with higher wages in larger firms (Oi and Idson 1999 wrote the handbook chapter on this literature). For example, Cardiff-Hicks et al (2014) show that even in recent years, large U.S. firms in the retail sector pay substantially higher wages than their smaller counterparts, while offering promotion potential into managerial occupations that smaller employers cannot offer.

However, a number of influential recent empirical studies demonstrate that large firms have growing importance in the United States, to the detriment of compensation for the majority of workers. Autor et al (2017) document that "superstar firms" are gaining market share in many sectors, and the industries where concentration rises most have the fastest falling labor share of output, due to the rapid expansion of these superstar firms. Song et al (2019) show that wage inequality has very different patterns within megafirms (those with 10,000 or more employees). Overall wage inequality growth is greater for workers in these firms, because wage inequality growth is happening within these firms, as well as between them (as in smaller firms). When their data begin in the early 1980s, these large firms had somewhat compressed wages compared with smaller firms (higher earnings for workers in the bottom half of the wage distribution), but that wage compression disappears by the end of their data series. Large firms see falling median wages, while smaller firms have rising median wages. Larger firms have much higher wage growth for their highest-paid workers than do smaller firms.

A new complementary literature shows the rising importance of employer monopsony power. Benmelech et al (2018) show that employer concentration at the county-industry level has been growing in the manufacturing sector, with a negative impact on wages, even after controlling for employer productivity, labor market size, and firm-by-year fixed effects. This relationship between employer concentration and wages is non-linear, and it is growing over time, but it is ameliorated in manufacturing industries with greater unionization rates. Lower competition among employers reduces the link between productivity growth and wage growth. Rinz (2018), Lipsius (2018), and Hershbein, Macaluso, and Yeh (2019) find similar relationships between employer concentration and wages to Benmelech et al across all sectors, although both of these papers find that employer concentration at the local level—in sectors other than manufacturing—has been declining over time. Rinz (2018) explains that this decline has happened as nationwide employers enter an increasing number of local markets. Similarly, Azar et al (2017) use online job posting data for 26 occupations to show a negative relationship between employer concentration at the occupation-commuting zone level and posted wages, and Sojourner and Qiu (2019) find a negative relationship between employer concentration and both wages and employment-based health insurance coverage. Meanwhile, Azar et al (2018) show wide variation in this type of employer concentration by occupation and geography, and Azar et al (2019) show a strong relationship between employer concentration and the elasticity of job applications to variation in posted wages in the same market, concluding that as many as 80% of workers are in markets with substantial monopsony power. Berger, Herkenhoff, and Mongey (2019) develop a detailed oligopsony model of the labor market, showing which measures of labor market power best capture the extent of competition in the labor market and that much of the measured correlation between employer monopsony power and wages is an artifact of market size.

In this paper, we use the microdata of BLS' Occupational Employment Statistics (OES) survey for May 2005 through May 2017, merged with the Quarterly Census of Employment and Wages (QCEW) to calculate measures of employer labor market power following three of these approaches in the literature. First, following Song et al., we can measure employer power by whether or not employers are megafirms. Second, we can measure employer power using a Herfindahl-Hirschman Index (HHI) of the employment by employer within each occupation in each geographic area, following Azar et al. Third, we can measure employer power using a Herfindahl-Hirschman Index of the employment by employer within each industry in each geographic area, following Benmelech et al. We construct all three of these measures for all occupations, industries, and geographic areas of the United States—for the private sector only and for all employment.

We show that employer power as measured by the HHI of occupations is remarkably similar—in levels, trends, and distribution across occupations and geographic areas—to employer power as measured by the HHI of industries, but both of these display remarkably different distributions and trends from the fraction of employment in megafirms.

Data Construction

The OES program surveys roughly 200,000 establishments each May and November. OES respondents report employment counts by detailed occupation and coarse wage bands. The sampling frame for this survey is the QCEW which records quarterly employment levels for each establishment in the US that reports to state-level Unemployment Insurance departments.[1] The sample design of the OES uses employment and wages collected from 1.2 million establishments over a 3-year period to create estimates of employment and wages for individual occupations at detailed levels of industry and geography.

Since we are expressly interested in employment concentration and the market power of megafirms, it is necessary to have a full accounting of employers by the domains of interest (i.e., industry, occupation, and geography). The QCEW is a census of employers and includes all the information necessary to construct measures of market power by geographic area and industry. A similar census of employers does not exist that would allow the investigation of the structure of labor markets defined by occupation and geographic area. To this end, we adapt the method of Dey, Piccone, and Miller (DPM) to map the OES microdata onto the full set of establishments in the QCEW in May of each year from 2005 through 2017.

The QCEW provides key determinants of the occupational staffing pattern and wages since it includes information about detailed industry, geographic area, and very importantly, the level of employment. Within the method, the QCEW can be divided into two parts, a seen part that includes units that were sampled by and responded to the OES survey and an unseen part that includes all other units. The DPM method estimates the labor market outcomes of non-responding units (the unseen part) using the occupation-specific information provided by OES respondents (the seen part).

Our version of the DPM method predicts the occupation-specific labor market outcomes for each non-responding unit using the observed outcomes from the single closest responding unit. In our version of the method, closeness is defined first and foremost by firm and detailed industry. Specifically, we attempt to find a responding unit that is in the same firm and detailed industry as the non-responding

[1] For more information on the coverage of the QCEW, see https://www.bls.gov/cew/cewbultn17.htm

unit in question. If we cannot locate a responding unit in the same firm and industry, we then search for a responding unit in the same detailed industry and since we are very likely to find respondents we choose the responding unit with the closest employment level to the non-responding unit. The end result of the DPM approach is a census of employers that includes employment levels and wages by detailed occupation.[2]

We identify firms using the Employer tax Identification Number (EIN) each establishment reports to the QCEW. Readers should be cautioned, however, that EINs are not good measures of firms in the QCEW data. Very large firms may use multiple EINs for their establishments in reporting their employment and wages to state unemployment insurance systems, the data that are then assembled into the QCEW data, and there is no straightforward way to link together all of the EINS used by these firms without a tremendous amount of manual review for each date. Thus, we may understate employer power—by every measure—by missing small EINs that are part of large firms. Further discussion of firm-EIN issues can be found in Handwerker and Mason (2013).

Each measure of employer power is calculated for each Metropolitan Statistical Area (MSA), as well as for the balance of state divisions of rural areas within each state that are used in drawing the OES sample.[3]

We make numerous small adjustments and aggregations of occupation and industry definitions to make these consistent from 2005 to 2017.

Let us define the set of employers as Ω and note that an employer is a collection of establishments that share the same EIN.

Employer Power Measure 1:

Following Song et al, we define megafirms as those employers with 10,000 or more employees associated with a single EIN, across all establishments in the QCEW. We define a megafirm flag M_e for each employer that equals 1 if employment at employer e is greater than or equal to 10,000 and equals 0 otherwise.

Our first measure of market power is the fraction of industry i in geographic area g employment in megafirms. The measure is specifically defined as

$$MS_{ig} = \frac{\sum_{e \in \Omega} E_{eig} \times M_e}{\sum_{e \in \Omega} E_{eig}}$$

[2] Federal and State Government employment is included in the OES data by occupation, wage level, and county of employment, but it is generally not split out into individual establishments. Local government employment in education, hospitals, and casinos is estimated for individual establishments (using the same methods as private sector employment); other local government employment is estimated at the county level.

[3] The counties used in defining each nonmetropolitan area are listed at https://www.bls.gov/oes/current/msa_def.htm We use these subdivisions of rural areas rather than the Commuting Zones used by Azar et al for two reasons. First, these subdivisions of rural areas are used by the OES program in drawing the OES sample, and so the sample sizes and sample distribution will be more uniform across rural areas if we use these subdivisions. Second, Foote, Kutzbach, and Vilhuber (2017) document that the boundaries of commuting zones in rural areas are estimated with a great deal of sensitivity to errors in the underlying data on worker commutes.

where E_{eig} represents employment in employer e, industry i, and geographic area g. Similarly, we define the fraction of occupation j in geographic area g employment in megafirms as

$$MS_{jg} = \frac{\sum_{e \in \Omega} E_{ejg} \times M_e}{\sum_{e \in \Omega} E_{ejg}}$$

where E_{ejg} represents employment in occupation j, area g, and employer e. Similarly we define the fraction of employment in geographic area g in megafirms as

$$MS_g = \frac{\sum_j \sum_{e \in \Omega} E_{ejg} \times M_e}{\sum_j \sum_{e \in \Omega} E_{ejg}} = \frac{\sum_{e \in \Omega} E_{eg} \times M_e}{\sum_{e \in \Omega} E_{eg}}$$

where E_{eg} represents employment in employer e and geographic area g. Lastly, we define the fraction of total employment in megafirms as

$$MS = \frac{\sum_g \sum_{e \in \Omega} E_{eg} \times M_e}{\sum_g \sum_{e \in \Omega} E_{eg}} = \frac{\sum_{e \in \Omega} E_e \times M_e}{\sum_{e \in \Omega} E_e}$$

where E_e represents total employment in employer e.

Overall, in our data, 21% of workers in May 2013 were employed in businesses (measured at the EIN level) with total employment of 10,000 or more, and 17% of private-sector workers were employed in such large employers. This is close to the 23% Song et al estimate for 2013 (the most recent year in that paper), calculated from IRS data.

Employer Power Measure 2:

Following Azar et al, but guided by the theoretical foundation of Berger et al, we calculate a Herfindahl-Hirschman Index of payroll by employer within each occupation for each geographic area. Specifically, we define the measure of occupation-area labor market concentration as

$$HHI_{jg} = \sum_{e \in \Omega} \left(s_{ejg}\right)^2$$

where $s_{ejg} = \frac{Y_{ejg}}{\sum_{e \in \Omega} Y_{ejg}}$ is the share of total wages paid in occupation j and geographic area g by employer e and Y_{ejg} denotes wages of employer e in occupation j and geographic area g.

This expands on the 26 occupations of Azar et al (2017) and the 200 occupations of Azar et al (2018). It also differs substantially from both Azar et al papers in estimating this measure for current payroll, rather than for new job postings.

As shown in Table 1, the average value of this measure is 0.088. We can also calculate an employment (rather than payroll) version of this measure for comparison to other authors. In our data, for the 26 occupations of Azar et al (2017), the employment-weighted level of the employment HHI measure is 0.051, compared with the 0.3157 calculated on an annual basis in Azar et al (2017). Azar et al (2017) note on page 9 that estimates (such as ours) based on employed workers should be lower than the concentration measures they estimate for vacancies. Across all occupations, we estimate an employment-weighted level of employer power HHI_{jg} of 0.101, which is lower than the 0.1638, weighted by employment in Azar et al (2018). Note that the average level of this variable in Azar et al

(2017) for only 26 occupations is lower than the level Azar et al (2018) calculate for 200 occupations, and this is also true for our estimates.

Employer Power Measure 3:

Following Benmelech et al. as well as Rinz and Lipsius, we calculate a Herfindahl-Hirschman Index of the payroll by employer within each industry in each geographic area. We differ from Benmelech et al, Rinz, and Lipsius, instead following Berger et al, by using payroll rather than employment in this index. The measure is specifically defined as

$$HHI_{ig} = \sum\nolimits_{e \in \Omega} \left(s_{eig}\right)^2$$

where $s_{eig} = \frac{Y_{eig}}{\sum_{e \in \Omega} Y_{eig}}$ is the labor market share of employer e in industry i and geographic area g. Benmelech et al and Rinz calculate employer power at the 3 and 4-digit SIC level and find similar results for these two levels of aggregation; we use 4 digit NAICS only. As shown in Table 1, the average value of this measure across all areas and industries is 0.174. We can also estimate an employment (rather than payroll) version of this measure, and for this measure we estimate average levels of 0.19 — slightly higher than the values in figure 2 of Rinz for 2005-2015 (approximately 0.15). For the manufacturing sector, we estimate average levels of this HHI measure of 0.36, which is lower than the 0.75 Benmelech et al estimate at the 3-digit SIC x county level.

Using the industry-occupation employment distribution for each geographic area, we can also estimate the weighted average value of the industry-area concentration measure for each occupation in each geographic area. This measure is defined as

$$\widetilde{HHI}_{jg} = \sum\nolimits_{i} \pi_{jig} \times HHI_{ig}$$

where π_{jig} is the share of employment in occupation j for industry i and geography g. This allows us to examine the correlation between this measure and the other two measures of employer power at the occupation level.

Defining “Oligopsonists”

Our first measure of employer power is discrete: We can classify employers as either megafirms or not megafirms. In contrast, our second and third measures of employer power are continuous measures of employer power for specific occupations or industries within a geographic area. To examine the overlap between megafirms and oligopsonists, or between megafirm employees and oligopsonist employees, (or to compare the share of employees in megafirms with the share of employees in oligopsonists) we need a discrete definition of oligopsonists.

We borrow from the work of the Antitrust Division of the U.S. Department of Justice, which considers 0.15 as the threshold for a “moderately concentrated” product market and 0.25 as the threshold for a “highly concentrated” product market.[4] For each labor market—whether defined by an occupation and

[4] These thresholds are given at https://www.justice.gov/atr/herfindahl-hirschman-index

geographic area or by an industry and geographic area—with at least 100 people employed, we rank employers by payroll, from largest to smallest, and sum their squared employment shares. We consider those whose summed payroll shares first reach 0.15 or 0.25 as oligopsonists in that particular market. For example, if one employer employs half the payroll (or if two large employers each employ 35.4% of the payroll) in a particular occupation and geographic area, we consider that employer the sole oligopsonist by the 0.25 threshold in that particular market; we would not call any other employer in that occupation and geographic area an oligopsonist at that threshold. By these definitions, an employer can be an oligopsonist in one geographic area, industry, or occupation, but not in other geographic areas, industries, or occupations. However, we can identify the employers that are ever oligopsonists, for comparison with megafirm employers.

Wage Variance Trends

Song et al find greater wage inequality growth for workers in megafirms than for workers in smaller firms, because wage inequality growth is happening within these firms, as well as between them (as in smaller firms). This pattern is also present in our data. Overall wage variance is greater and is growing faster for the employees of megafirms than for the employees of smaller firms. There is greater and growing wage variance within megafirm employers, but no wage variance growth within smaller employers.

We do not find similar differences in wage variance growth between workers in the most concentrated labor markets (as measured by either HHI measure) and other workers. Since about 17% of private-sector workers are employed in megafirms, Figure 1 shows wage variance trends for the 17% of workers in the most concentrated labor markets, compared with other workers. Notably, there is lower wage variance, overall and within employers, for the workers in more highly-concentrated labor markets, and no difference in either form of wage variance growth.

Distributions of Employer Power

By geography

Figure 2 maps average values for all three measures of employer power by Metropolitan Statistical Area/Balance of State areas. The fraction of employment in megafirms is generally higher in the south and in state capitals (due to the inclusion of state governments as megafirms). Patterns are very different for average values of the Herfindahl-Hirschman Indices by either industry or occupation; these indices have high and low values scattered around the country, although particularly high concentration levels by industry generally occur in the same geographic areas as high concentration levels by occupation.

Taking average levels of the Herfindahl-Hirschman Indices at the CBSA/BOS level, the two different measures of payroll concentration have a correlation of 0.9696, but the share of employment in megafirms at the CBSA/BOS level has a correlation of 0.02 with the average occupation-based HHI index and 0.00 with the average Industry-based HHI index. This is illustrated graphically in Figure 3.

Azar et al (2018) first noted higher levels of employer concentration in rural areas—which Berger, Herkenhoff and Mongey (2019) show is a consequence of the higher levels of investment and employment in more productive areas, even without the exercise of oligopsony power. We find similarly that both HHI measures of employer power are negatively correlated with population density, while the fraction of employment in megafirms is positively correlated with the population density of a geographic area. This is illustrated graphically in Figure 4. Table 1 shows that both HHI measures (occupation-based and industry-based) are substantially higher in Balance- of- State areas than in metropolitan areas, while the fraction of employment in megafirms is higher in metropolitan areas than in these rural areas. This pattern of higher HHI indices in areas with smaller population—with no such clear pattern for the fraction of employment in megafirms—is illustrated quite clearly in Figure 4.[5]

We find that there is a strong negative correlation between the level of employer concentration by either HHI measure and the average level of wages in a geographic area (correlations of -0.41 for the occupation-HHI and -0.49 for the industry-HHI), while there is a strong positive correlation between the fraction of employment in megafirms and the wage level (correlation of 0.34). Berger, Herkenhoff, and Mongey (2019) point out that the relationship between HHI indices and wages by area arises from the higher productivity in areas attracting more investment and employment.

Examining the correlation of trends in these measures, the areas with increasing fractions of employment in megafirms are generally the same areas with increasing levels of employer concentration, by either HHI measure. However, an increasing share of employment in megafirms is correlated with rising wages, while increasing levels of employer concentration are correlated with falling wages.

By occupation

Figure 4 maps average values in 2017 for the first and second measures of employer power, using the discretized version of oligopsony (at the .15 threshold). Overall, figure 4B shows that the greater the total employment in an occupation, the smaller the share of people in that occupation employed by a local oligopsonist (although there is far more variation around this trend for occupations than there is for geographic areas—a reason to further investigate the determinants of oligopsony power by occupation). In contrast, there is little relationship between the size of an occupation and the fraction of that occupation employed in megafirms.

Examining the share of employment in megafirms and oligopsonists by the average ln(wage) of occupations, Figure 4C shows opposing patterns for megafirms and monopsonist employment. The range of occupational average wages in which the share of employment in oligopsonists is increasing is the same range of occupational average wages in which the share of employment in Megafirms is decreasing—and vice versa.

Figures 4B and 4C also show that very little of the variation between occupations in the fraction of employment in megafirms or oligopsonists can be explained by either the size of the occupation or the average wage in the occupation. Using the microdata underlying these figures, we can examine this

[5] This figure is drawn for all employers in the second quarter of 2017. It is virtually indistinguishable from similar figures drawn for private sector employers only, or from figures drawn for other years.

further. For the private sector, a regression of occupation size and its square on being employed in an oligopsonist has an R^2 value of 0.02, and a similar regression of occupation fixed effects on being employed in an oligopsonist has an R^2 value of .143. Meanwhile, similar regressions on being employed in a megafirm has an R^2 value of .101. Adding in geographic area and geography*year fixed effects raises the R^2 value for the oligopsonist regression to .174, but has little impact on explaining megafirm employment (the R^2 value is .115). Further adding in industry fixed effects raises the R^2 value for the oligopsonist regression to .212, while the R^2 value for the megafirm regression increases to .316. MSA has a greater role in explaining oligopsonist employment than megafirm employment, while industry has a far greater role in explaining the megafirm employment than oligopsonist employment.

Examining the occupation fixed effects in these same regressions, different patterns emerge for regressions on oligopsonist employment and on megafirm employment. The average absolute value of these coefficients in a regression on oligopsony employment is about .19, whether or not geographic area and geography*year fixed effects are included, and falls to .159 once industry fixed effects are added. For a regression on megafirm employment, the absolute value of the coefficients for the occupation fixed effects is about .165, whether or not geographic area and geography*year fixed effects are included, but falls to .049 once industry fixed effects are added. This suggests that much of the difference between occupations in employment in megafirms (within the private sector) can be attributed to differences in the industries in which these occupations are employed, and this is not true for employment in oligopsonists.

It is straightforward to link these occupations with their characteristics in the O*Net data. We use the aggregations of occupational characteristics from Dey and Loewenstein to examine whether these characteristics can explain the residual variation among occupations in how much of their employment is in oligopsonists and megafirms. Specifically, we take the occupation fixed effect coefficients βo from regressions of the form

$\text{Oligopsonist or megafirm}_{eijgy} = \beta_{oj} * \text{occupation}_j + \beta_{o1} * \text{occupation size}_j + \beta_{o2} * \text{occupation size}^2_j + \beta_{g1} *\text{geographic area}_g + \beta_{g2} *\text{geographic area}_g * \text{year}_y + \beta i * \text{industry}_i + \beta_{e1} * \text{Employer size}_e + \beta_{e2} * \text{Employer size}^2_e + \varepsilon_{jigy}$, where an indicator for employment in a local oligopsonist or a megafirm is regressed on occupation fixed effects, occupation size, occupation size squared, geographic area fixed effects, geography * year fixed effects, industry fixed effects, EIN size, and EIN size squared. These regressions are run for the private-sector only, in occupations and local areas for which there are at least 100 people employment in the occupation within the local area. We then examine whether any of the variation in the resulting occupation coefficients can be explained using the occupation characteristic aggregations from Dey and Loewenstein (2019). The results are shown in Table 2. We find these occupational characteristic aggregations explain 15% of the residual variation among occupations in whether people are employed by oligopsonists, and only 6% of the residual variation among occupations in whether people are employed in megafirms. However, the occupational characteristics that most predict employment in oligopsonists are largely different from the occupational characteristics that predict employment in megafirms. Of particular note, the occupational characteristic most strongly positively associated with employment by an oligopsonist (after controlling for geography, occupation size, the industry of the employing establishment and so forth) is Dey and Loewenstein's "Working Conditions4," which involves exposure to disease, infections, and radiation. This is a characteristic of occupations in the medical field, such as doctors, nurses, and health technicians, and these particular occupations have been the subject of studies of employer consolidation, such as Prager and Schmitt (2019).

Megafirms compared with oligopsonist employers

Using the discrete definitions of megafirms and oligopsonists (by area-occupation) described above, less than 0.3% of employers (defined by EINs) are either megafirms or oligopsonists (at the .25 threshold) in any labor market. There are about 13,000 EINs that are ever an oligopsonist in any market. Of these, about 3,000 are local governments. 625 EINs are both megafirms and oligopsonists in at least one market. These include the federal government and every state government, as well as several dozen large local governments. An additional 300 EINs (including a handful of local governments) are megafirms but not oligopsonists in any market. By the .15 threshold, there are about 28,000 EINs that are ever an oligopsonist in any market, of which about 5,000 are local governments. Even at this more relaxed threshold for defining oligopsonists, less than 0.6% of employers that ever employ 100 people in an occupation within a geographic area are either a megafirm or an oligopsonist in any of these markets.

Turning to employment, 76% of workers are employed at EINs that are neither megafirms nor oligopsonists (in their particular geographic area and occupation), using the .25 threshold for oligopsonists, and this falls to 74% using the .15 threshold for oligopsonists. Loosening the definition of oligopsonist employment adds many more private-sector employees than government-sector employees. 94% of the workers in megafirm-oligopsonists are in the public-sector when we use the .25 threshold to define oligopsonists, and 60% are public-sector employees when we use the .15 threshold.

Using the more relaxed definition of oligopsony employment, the most common occupations for the 74% of workers (of which 10% work for local governments) employed by non-megafirms/non-oligopsonists are Combined Food Preparation and Serving Workers, Retail Salespeople, General Office Clerks, Waiters and Waitresses, and Registered Nurses. 18% of workers are employed in megafirms that are not oligopsonists (of which 21% work for governments). The most common occupations among these megafirm/non-oligopsonist workers are Retail Salespeople; Cashiers; Stock Clerks and Order Fillers; Laborers and Freight, Stocks and Material Movers; and Customer Service Representatives. 2% of workers are employed in oligopsonists that are not megafirms (of which 33% work for local governments). The most common occupations among these oligopsonist/non-megafirm workers are Registered Nurses, Elementary School Teachers, Secondary School Teachers, Other Teachers, and Teacher Assistants. 2% of workers are employed in oligopsonist megafirms (of which 94% work for governments). The most common occupations among these oligopsonist megafirm workers are Personal Care Aides, Postal Service Mail Carriers, Correctional Officers, Registered Nurses, and Other Business Operations Specialists.

The overlap of megafirm with oligopsonist employment is disproportionately a description of government employment. To our knowledge, this has not previously been addressed in the literature on employer power.

Overall Trends in Employer Power

Figure 5 shows trends in all of these measures of employer power from 2005 to 2017, both the actual levels measured, and the levels we would observe if employment in each Metropolitan/Balance-of-State area x 4-digit NAICS industry combination or Metropolitan/Balance-of-State area x 6-digit SOC occupation had remained constant.

Consistent with the findings of Song et al, we find that the fraction of employment in megafirms is increasing over time. This increase is not explained by changes in the distribution of employment between industries and areas and only partially explained by changes in the distribution of employment between occupations and areas; even if these were unchanged, there would be still be increases over time in the fraction of employment in very large EINs.

Consistent with the findings of Rinz and Lipsius, we find that employer concentration as measured by the Herfindahl-Hirschman Index of payroll (or employment) by industry within each geographic area is decreasing over time. However, much of this decrease has come from shifts of employment from sectors and areas with higher levels of employer concentration to sectors and areas with lower levels of employer concentration. (In results not shown, we look at this measure for the manufacturing sector only, as in Benmelech et al, and find an increase over time)

We also find that employer concentration as measured by the HHI of payroll by occupation within each geographic area is falling over time. This fall was driven in 2005-2008 by changes in concentration within local labor markets, not by shifts in employment between these markets. However, by 2017 the actual decline in employment concentration was very similar in 2017 to what it would have been if the shares of employment in each local labor market were the same as they had been in 2005.

Conclusion

In an environment of rising employment with little wage growth, economists are paying increased attention to factors that might reduce wage growth. Two of these are the growing and changing role of very large firms in the labor market and the role of monopsony power in the labor market. The growth of large employers could overlap with growing monopsony power in local labor markets for these same employers. However, this paper shows that the employment trends and distribution of very large employers are quite distinct from the employment trends and distribution of employers with local labor market power in the U.S. economy during 2005-2017.

Using new methods to map the detailed occupation and wage distribution microdata of the Occupational Employment Statistics onto the employment histories of nearly every establishment in the United States for 2005-2017, we replicate some of the main measures of employer power from Song et al (2019), Benmelech et al (2018), Rinz (2018), Lipsius (2018), Azar et al (2017), and Azar et al (2018). We show that while the amount of employment in megafirms is growing over time, the average level of Employment Concentration—measured by Herfindahl-Hirschman Indices of employment by employer at the detailed industry within geographic area or detailed occupation with geographic area—is falling over time. We show that while the employees of megafirms have higher and growing wage variances than the employees of smaller employers, explained by rising wage inequality within these large employers, workers in highly concentrated labor markets have less wage variance and less wage variance within employers than workers in less concentrated labor markets, but similar trends in wage variance growth over time. We show that geographic areas with large shares of employment in megafirms are generally different areas than the areas with high levels of employment concentration, and this is not fully explained by employment size. Similarly, occupations with large shares of employment in megafirms are generally different than occupations with large shares of employment in local oligopsonists, and even less of this difference can be explained by occupation size.

We further show that the overlap between very large employers and employers that are explicit oligopsonists in specific labor markets is disproportionately made up of public-sector employers, who employ more than half of the workers in megafirm-oligopsonist employment. This empirical fact has not been addressed elsewhere by the rapidly growing literature on employers with this type of labor market power.

The next steps in this (still incomplete) research project are twofold:

(1) We have more work to do to explain why employment has been shifting into non-oligopsonist megafirms over the period we study. In the analysis depicted in Figure 5, we have separately examined the impact of changes in employment by geography & industry and the impact of changes in employment by geography & occupation, but we have not examined the impact of changes in all three of these factors. Nor have we measured the impact of employer mergers on any of our measures of employer power (although we are well aware that many mergers of ownership do not result in mergers of the EINs used for the unemployment insurance system that appear in our data).

(2) The great advantage of using our data to study employer power is the richness of its occupational measures within geographic areas and industries. We are able to show, for example, that after accounting for industry and geographic differences, occupations involving administrative tasks are less frequently employed by oligopsonistic employers, while occupations involving exposure to disease and radiation are more frequently employed in local oligopsonists. These same occupational characteristics appear to have no relationship (after accounting for industry and geographic differences) with the likelihood of employment in megafirms. In future work, we plan to borrow the methodology developed in the several papers by Azar, Marinescu, and Steinbaum (2017, 2018, 2019), as well as in Berger, Herkenhoff, and Mongey (2019), to learn which occupations have wages most affected by a greater extent of employer power in local geographic areas, and whether these occupations have any particular characteristics in common.

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Table 1. Summary measures of Concentration and Megafirms

	All areas	MSAs	Balance of State Areas
Number of year-area observations	7,085	4,979	2,106
Average number of establishments per area-year	13,010	15,924	6,119
Average number of firms per area-year	10,536	12,792	5,204
Average employment per area-year	241,632	301,905	99,133
Average establishments per firm	1.18	1.19	1.17
Average workers per firm	21.71	23.00	18.67
Average real (2017$) mean wage	$18.75	$19.34	$17.36

Average payroll concentration (HHI at the occupation-area level)

	Unweighted			Weighted (by area employment)		
Statistic	All areas	MSAs	Balance of State Areas	All areas	MSAs	Balance of State Areas
Mean	0.155	0.162	0.138	0.088	0.084	0.117
SD	0.069	0.070	0.063	0.055	0.056	0.039

Average payroll concentration (HHI at the industry-area level)

	Unweighted			Weighted (by area employment)		
Statistic	All areas	MSAs	Balance of State Areas	All areas	MSAs	Balance of State Areas
Mean	0.281	0.293	0.253	0.174	0.167	0.229
SD	0.098	0.104	0.077	0.092	0.094	0.052

Megafirm share of employment

	Unweighted			Weighted (by area employment)		
Statistic	All areas	MSAs	Balance of State Areas	All areas	MSAs	Balance of State Areas
Mean	18.890	20.552	14.962	21.376	22.269	14.951
SD	6.478	6.348	4.895	5.369	4.903	4.042

Table 2: Regressions of occupation characteristics from Dey and Loewenstein (2019) on residual occupation fixed effects

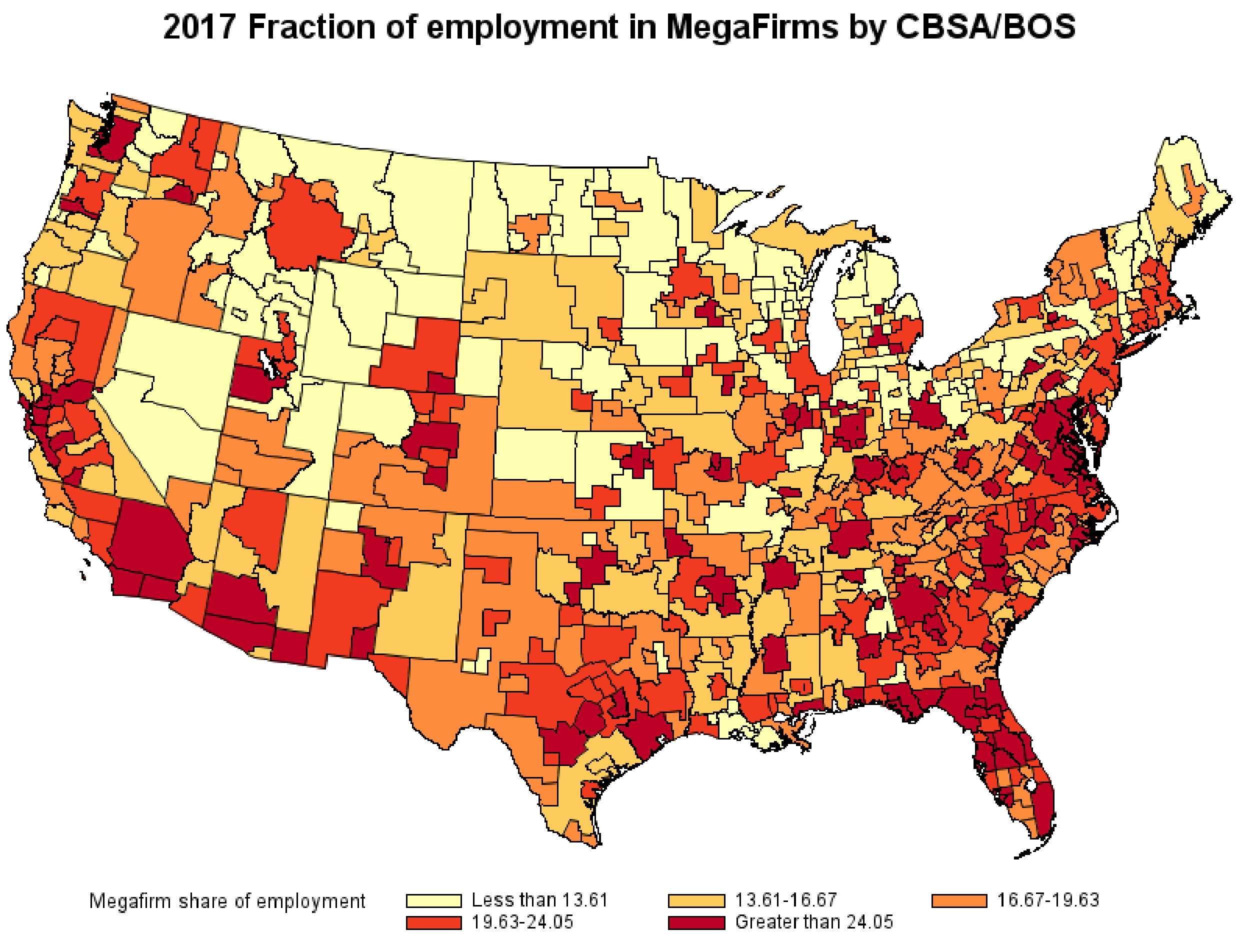
	Oligopsony	MegaEIN
General cognitive skills	0.016	0.007
	(0.010)	(0.004)
Quick thinking skills	-0.013	0.006*
	(0.007)	(0.003)
Visual and hearing skills	0.021*	0.003
	(0.010)	(0.004)
Speaking skills	0.014	-0.009**
	(0.008)	(0.003)
Managerial tasks	-0.003	-0.000
	(0.008)	(0.003)
Sales and communications	-0.020**	0.004
	(0.007)	(0.003)
Work with machinery	-0.004	-0.006
	(0.008)	(0.003)
Interacting with computers	0.005	0.010**
	(0.009)	(0.003)
Administrative tasks	-0.044***	0.002
	(0.009)	(0.004)
Customer services	-0.001	0.002
	(0.005)	(0.002)
Responsibility and leadership	-0.003	0.004
	(0.005)	(0.002)
Hazardous working conditions	0.003	-0.004
	(0.007)	(0.003)
Time on one’s feet	-0.017*	-0.003
	(0.008)	(0.003)
Physically repetitive tasks	-0.006	0.000
	(0.006)	(0.002)
Exposure to disease & radiation	0.016**	-0.003
	(0.005)	(0.002)
Decision making	-0.015**	-0.007**
	(0.006)	(0.002)
Repetitive manual work	0.001	0.001
	(0.005)	(0.002)
Gross motor skills	0.016	0.009*
	(0.009)	(0.004)
Fine motor skills	-0.023*	-0.004
	(0.011)	(0.004)
Monitoring tasks	0.010	0.011**
	(0.008)	(0.003)
Data analysis & problem solving	-0.001	-0.017**
	(0.013)	(0.005)
Constant	-0.150***	-0.023***
	(0.004)	(0.002)
R-squared	0.150	0.064
N	761	761

Notes: These are regressions of the occupation characteristic factors from Dey and Lowenstein (2019) on residual occupation fixed effects from regressions of the form Oligopsonist or megafirm$_{eijgy}$ = β_{oj} * occupation$_j$ + β_{o1} * occupation size$_j$ + β_{o2} * occupation size^2_j + β_{g1} *geographic area$_g$ + β_{g2} *geographic area$_g$ * year$_y$+ βi * industry$_i$ + β_{e1} * Employer size$_e$ + β_{e2} * Employer size^2_e + ε_{jigy}, Initial regressions are run on the OES microdata mapped to the QCEW, as described in the text, restricted to private sector labor markets of at least 100 people per occupation per geographic area. * p<0.05, ** p<0.01, *** p<0.001

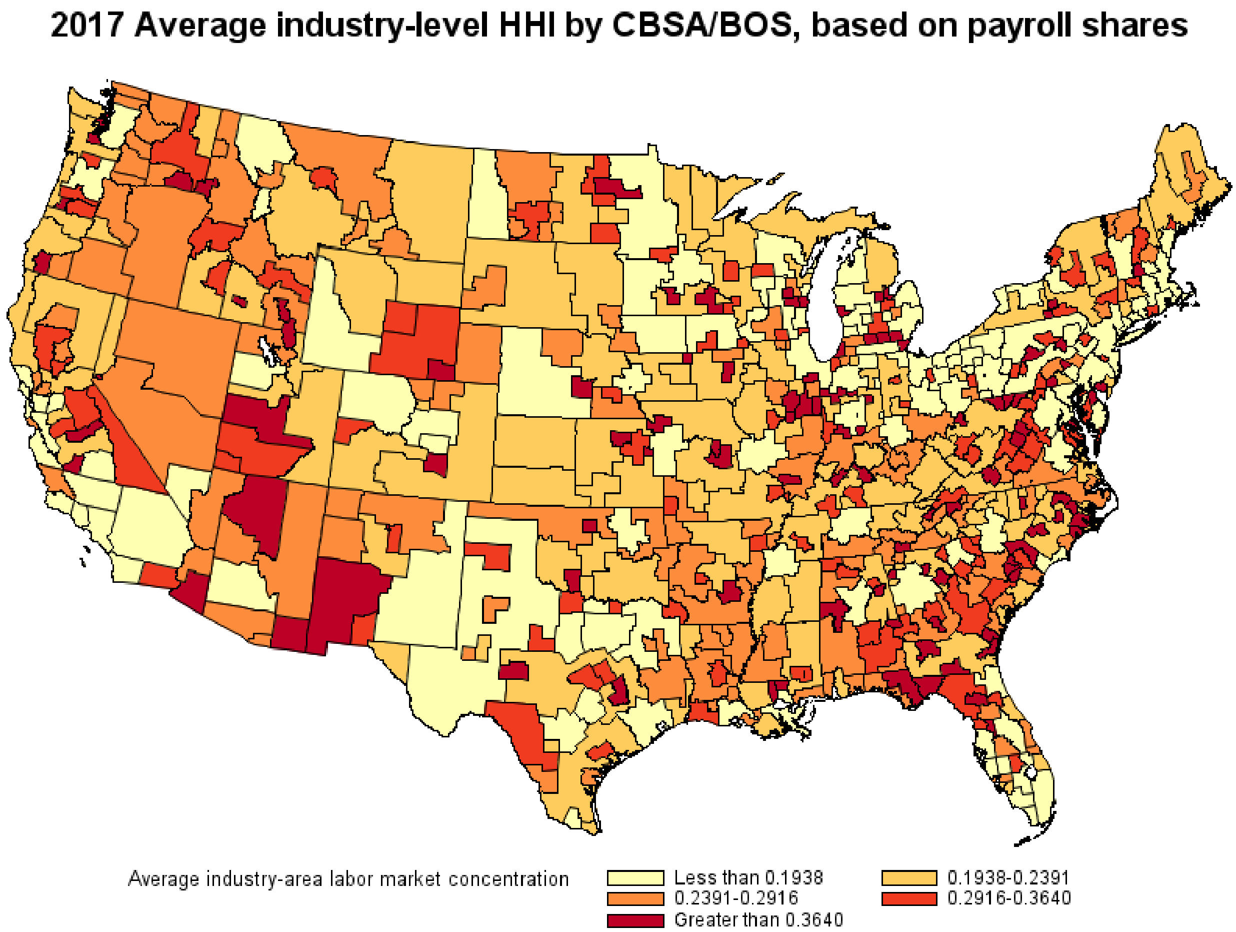
Figure 1: Overall and Within Employer Wage Variances by date and measure of Employer Power, 2005-2017

Notes: This figure shows total wage variance trends and within-EIN wage variance trends for employees of private-sector Megafirms (those with 10,000 or more employees, comprising 17% of private-sector employment) compared with employees of smaller employers, private-sector employees in area x occupation labor markets that are particularly highly concentrated (having employment in the top 17% of area x occupation HHI values) compared with private-sector employees in less concentrated labor markets, and private-sector employees in area x industry labor markets that are particularly highly concentrated (having employment in the top 17% of area x industry HHI values) compared with private-sector employees in less concentrated labor markets.

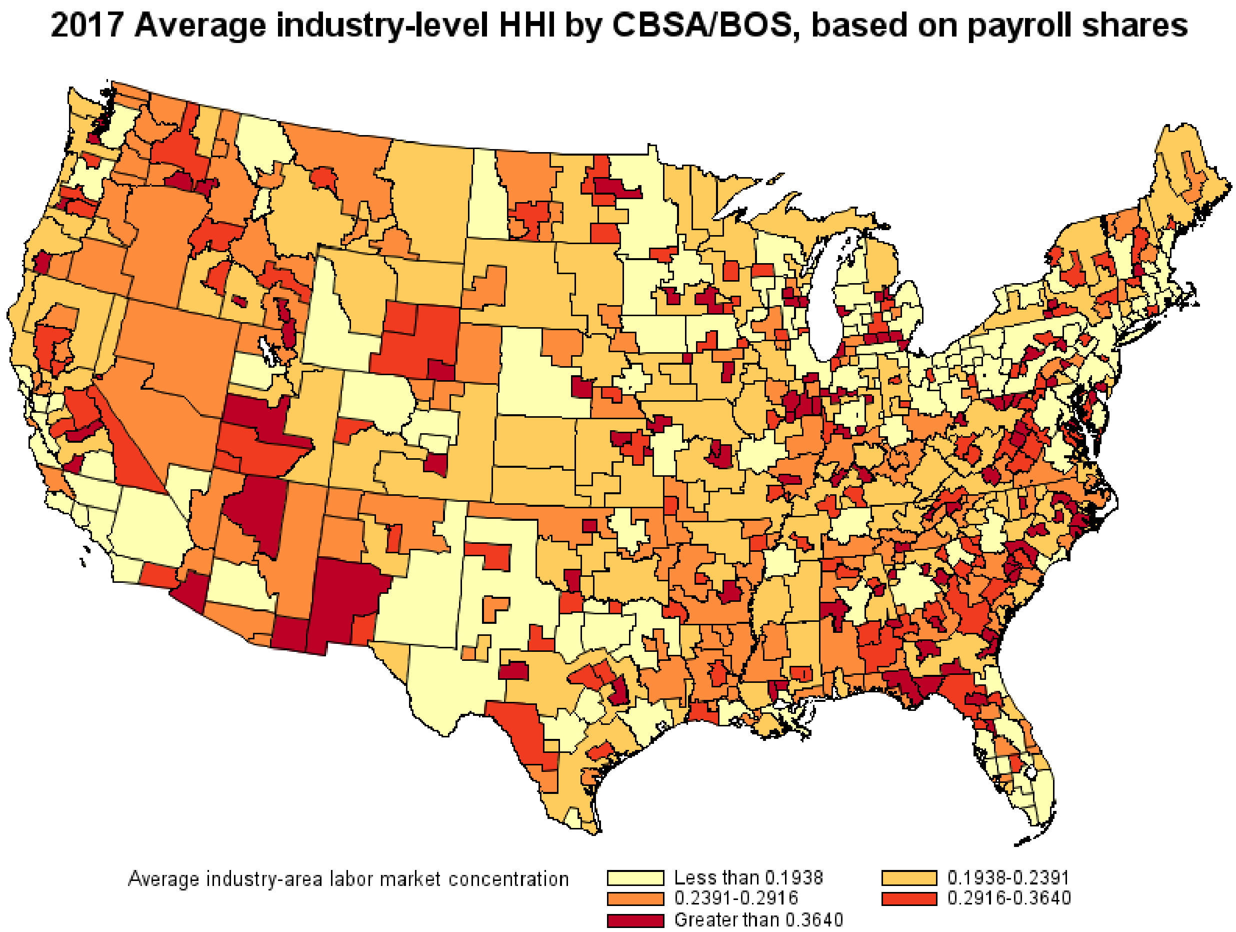
Figure 2: Average Measures of Employer Power, by MSA/Balance of State Area



This figure shows the average fraction of employment in "megafirms": EINs with nationwide employment of 10,000 or more, by Metropolitan Statistical Area or non-metropolitan Balance of State Areas in the 2nd quarter of 2017. Public sector employment is included in these totals, and federal and state governments are considered "megafirms" for this purpose. These data are from the BLS Quarterly Census of Employment and Wages.



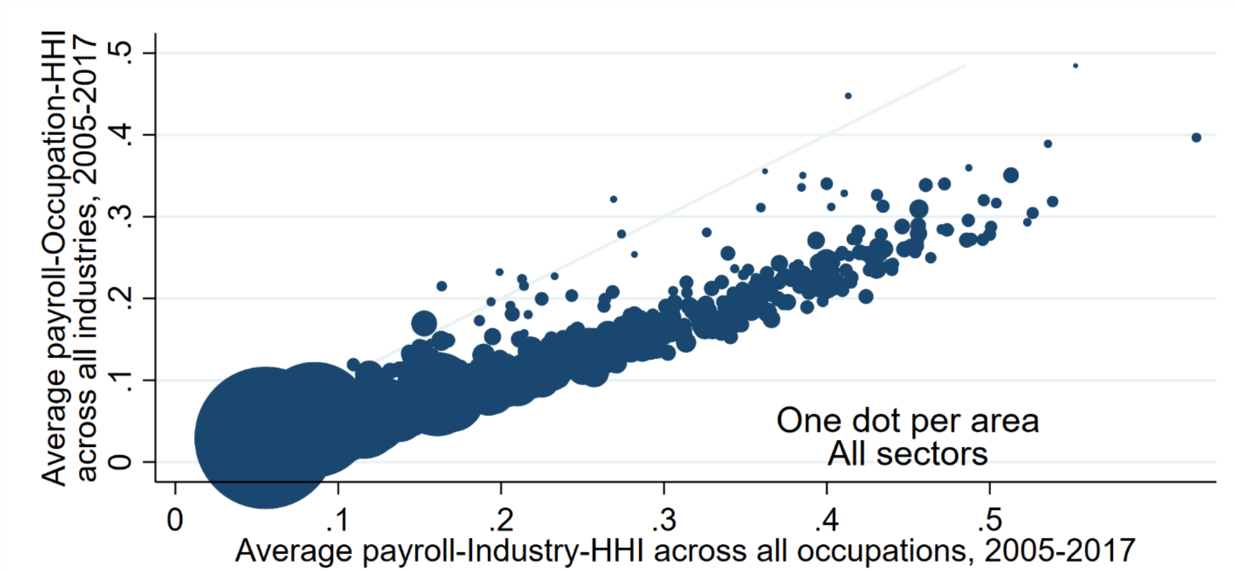
This figure shows the average of the Herfindahl-Hirschman Index of payroll by 6-digit occupation for labor markets, by Metropolitan Statistical Area or non-metropolitan Balance of State Areas in the 2nd quarter of 2017. Public sector employment is included in these totals. These data are from a complete projection of employment by occupation based on the BLS Occupational Employment Statistics Survey microdata onto all establishments in the BLS Quarterly Census of Employment and Wages.



This figure shows the average of the Herfindahl-Hirschman Index of payroll by 4-digit industry for labor markets, by Metropolitan Statistical Area or rural Balance of State Areas in the 2nd quarter of 2017. Public sector employment is included in these totals. These data are from a complete projection of employment by occupation based on the BLS Occupational Employment Statistics Survey microdata onto all establishments in the BLS Quarterly Census of Employment and Wages.

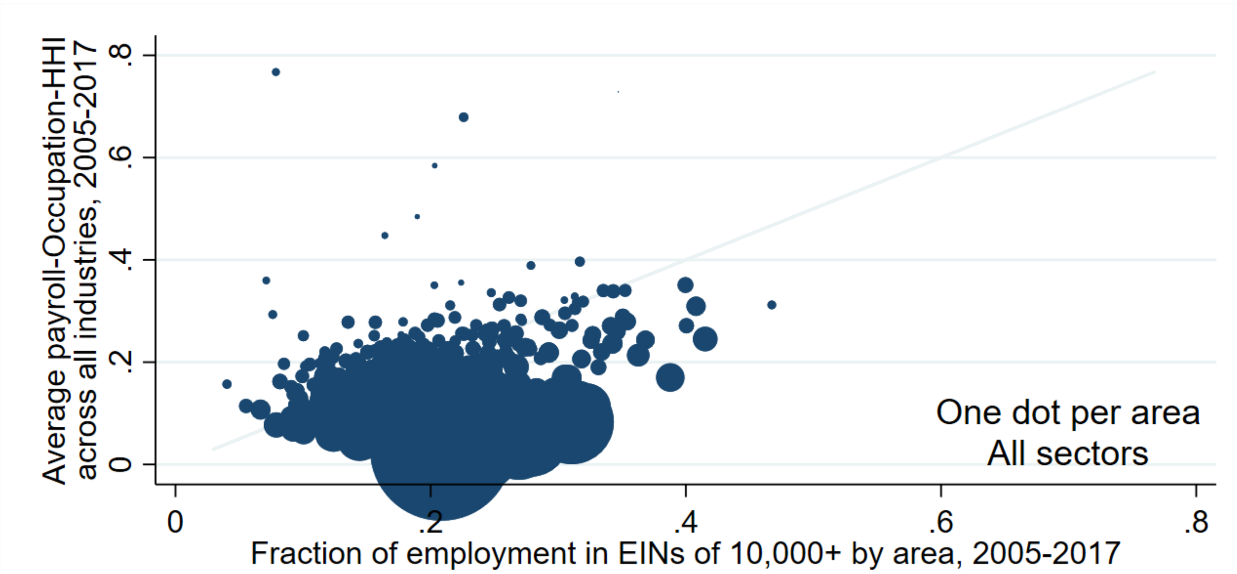
Figure 3: Correlations between measures of Employer Power

A: Occupation-based HHI (averaged across industries) and Industry-based HHI (averaged across occupations) averaged across years for each geographic area



This figure shows the average value of the Herfindahl-Hirschman Index of payroll across 4-digit industries for labor markets and across the average value of the Herfindahl-Hirschman Index of payroll across 6-digit occupations, by Metropolitan Statistical Area or rural Balance of State Areas in the 2nd quarter of 2017. Public sector employment is included in these totals. The size of each point corresponds to the average annual total employment in that geographic area. These data are from a complete projection of employment by occupation based on the BLS Occupational Employment Statistics Survey microdata onto all establishments in the BLS Quarterly Census of Employment and Wages.

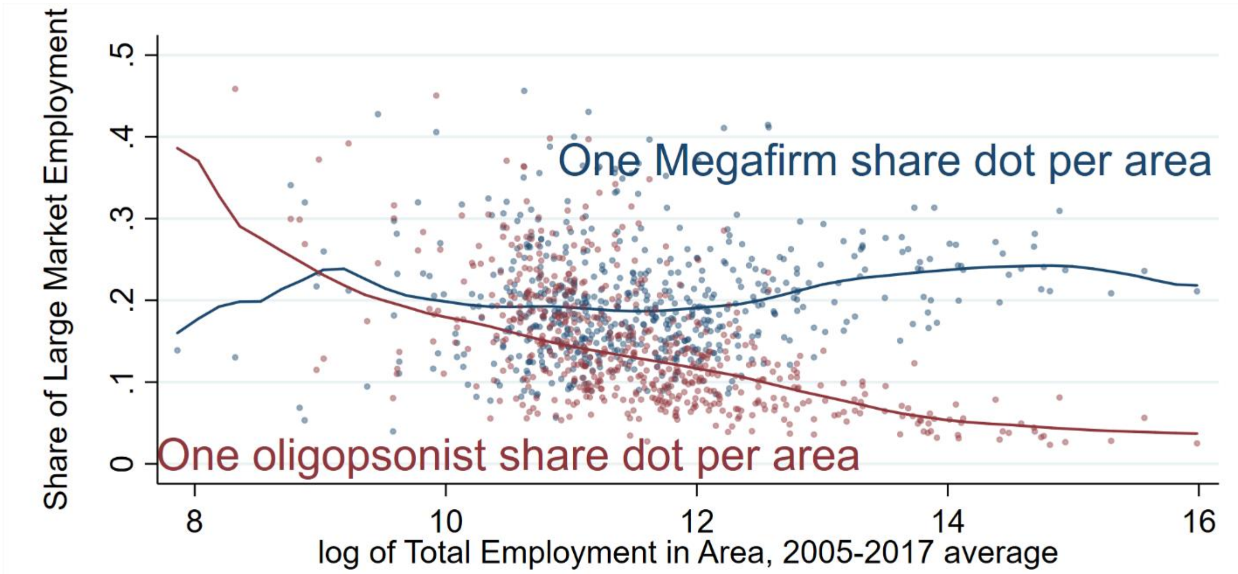
B. Occupation-based HHI (averaged across industries) and fraction of total employment in 'Megafirms' averaged across years for each geographic area



This figure shows the average value of the Herfindahl-Hirschman Index of payroll across 6-digit occupations and the fraction of employment in "megafirms": EINs with nationwide employment of 10,000 or more, by Metropolitan Statistical Area or rural Balance of State Areas in the 2nd quarter of 2017. Public sector employment is included in these totals. The size of each point corresponds to the average annual total employment in that geographic area. These data are from a complete projection of employment by occupation based on the BLS Occupational Employment Statistics Survey microdata onto all establishments in the BLS Quarterly Census of Employment and Wages.

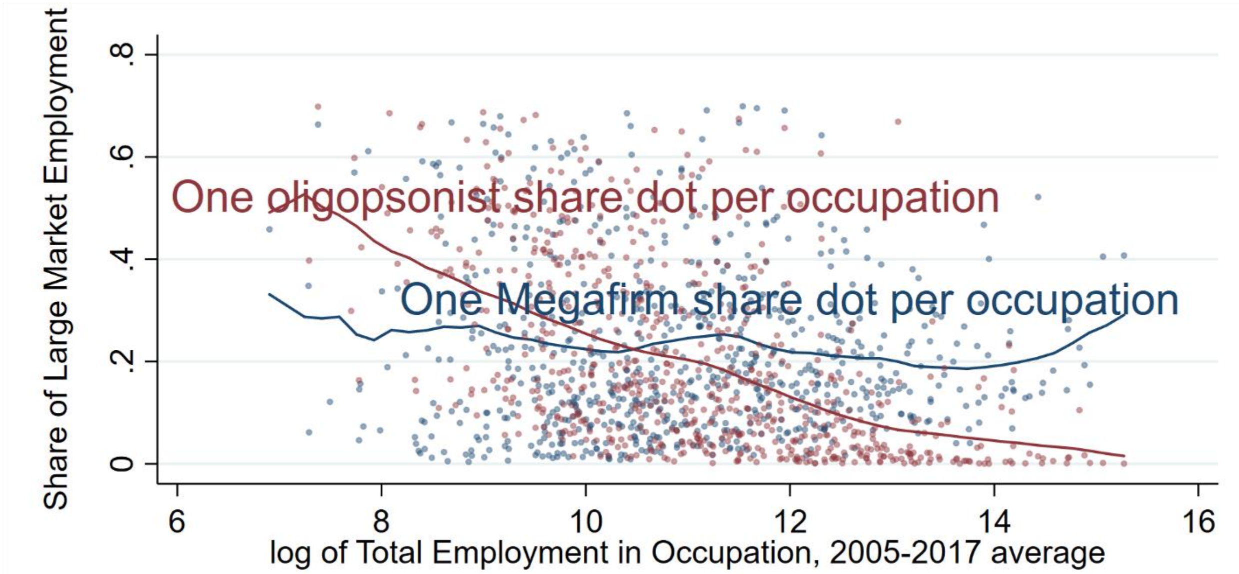
Figure 4: Share of Employment in 'Megafirms' and area-occupation-specific 'Oligopsonists,' averaged across areas or occupations.

A. Share of employment in Oligopsonists and 'Megafirms' by Area Size



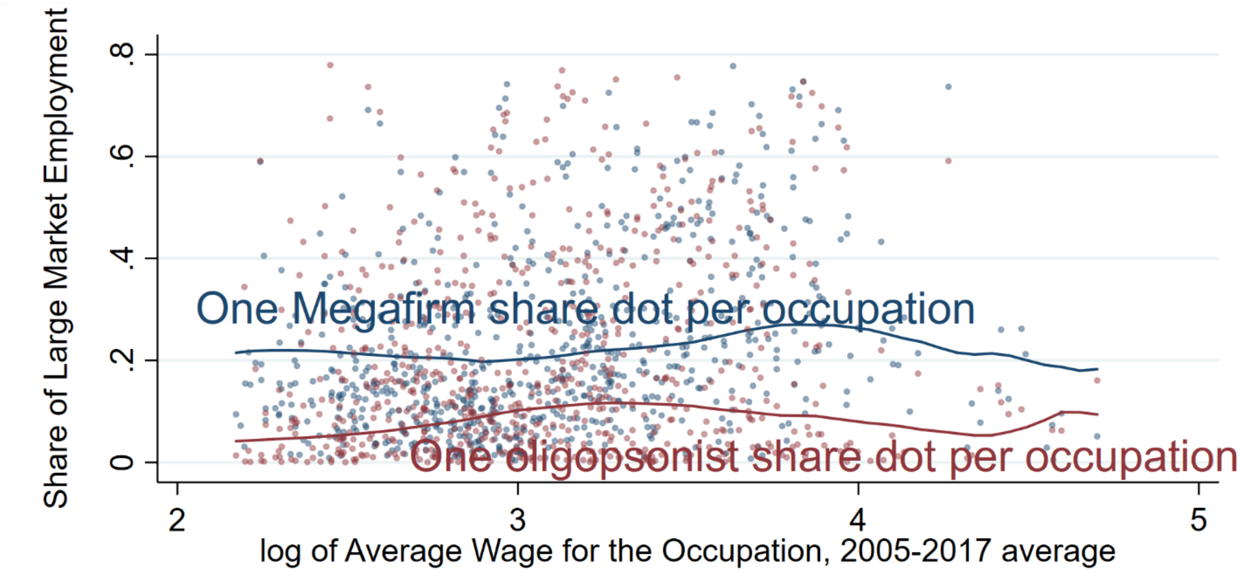
Notes: This figure shows the fraction of employment share of employment in "megafirms": EINs with nationwide employment of 10,000 or more, by Metropolitan Statistical Area or rural Balance of State Areas in the 2nd quarter of 2017. It also shows the fraction of employment in employers with squared payroll shares that sum to 0.15 or more, as described in the text, averaged across all occupations with 100 or more workers for each Metropolitan Statistical Area or Balance of State Area in the 2nd quarter of 2017. Public sector employment is included. There is one dot shown for each area. Lines are a weighted lpoly fit to all data, including points not shown because they are based on very few employers. These data are from a complete projection of employment by occupation based on the BLS Occupational Employment Statistics Survey microdata onto all establishments in the BLS Quarterly Census of Employment and Wages.

B. Share of employment in Oligopsonists and 'Megafirms' by Occupation Size



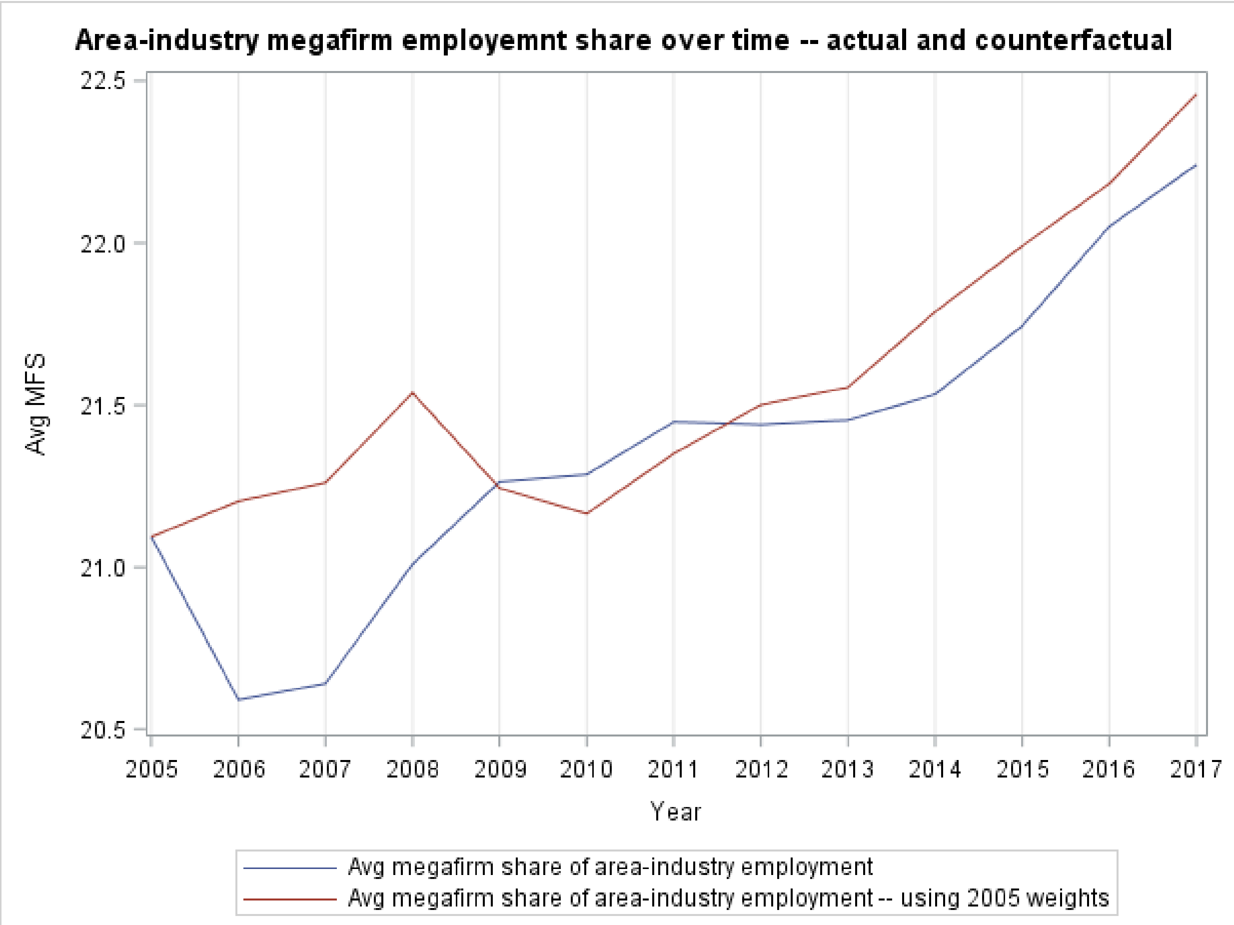
Notes: This figure shows the fraction of employment share of employment in "megafirms": EINs with nationwide employment of 10,000 or more, by occupations in the 2nd quarter of 2017. It also shows the fraction of employment in employers with squared payroll shares that sum to 0.15 or more, as described in the text, averaged across all geographic areas with 100 or more workers for each occupation in the 2nd quarter of 2017. Public sector employment is included. There is one dot shown for each area. Lines are a weighted lpoly fit to all data, including points not shown because they are based on very few employers. These data are from a complete projection of employment by occupation based on the BLS Occupational Employment Statistics Survey microdata onto all establishments in the BLS Quarterly Census of Employment and Wages.

C. Share of employment in Oligopsonists and 'Megafirms' by Occupation Average Wage

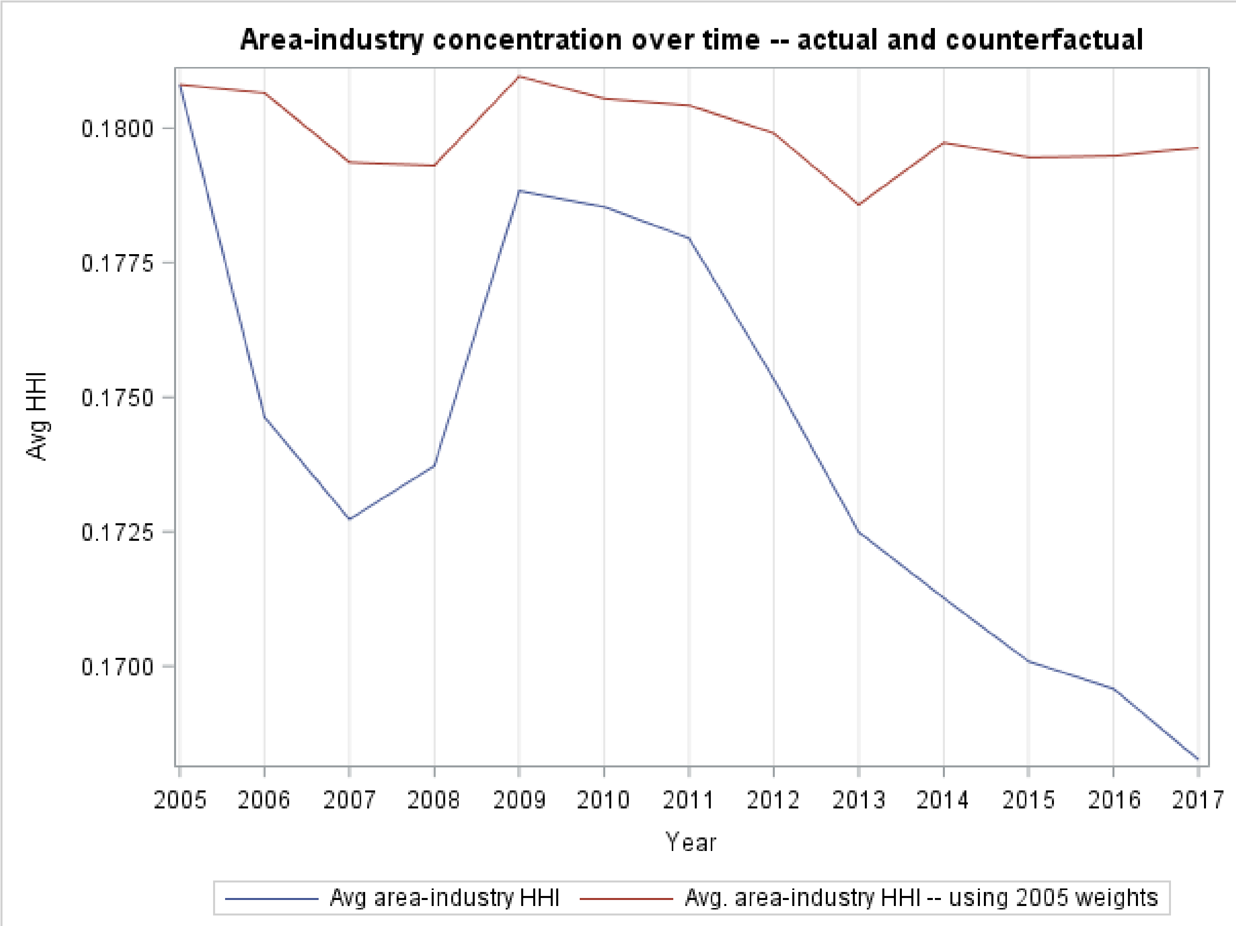


Notes: This figure shows the fraction of employment share of employment in "megafirms": EINs with nationwide employment of 10,000 or more, by occupations in the 2nd quarter of 2017. It also shows the fraction of employment in employers with squared payroll shares that sum to 0.15 or more, as described in the text, averaged across all geographic areas with 100 or more workers for each occupation in the 2nd quarter of 2017. Public sector employment is included. There is one dot shown for each area in which statistics are calculated based on 5 or more employers. Lines are a weighted lpoly fit to all data, including points not shown. These data are from a complete projection of employment by occupation based on the BLS Occupational Employment Statistics Survey microdata onto all establishments in the BLS Quarterly Census of Employment and Wages.

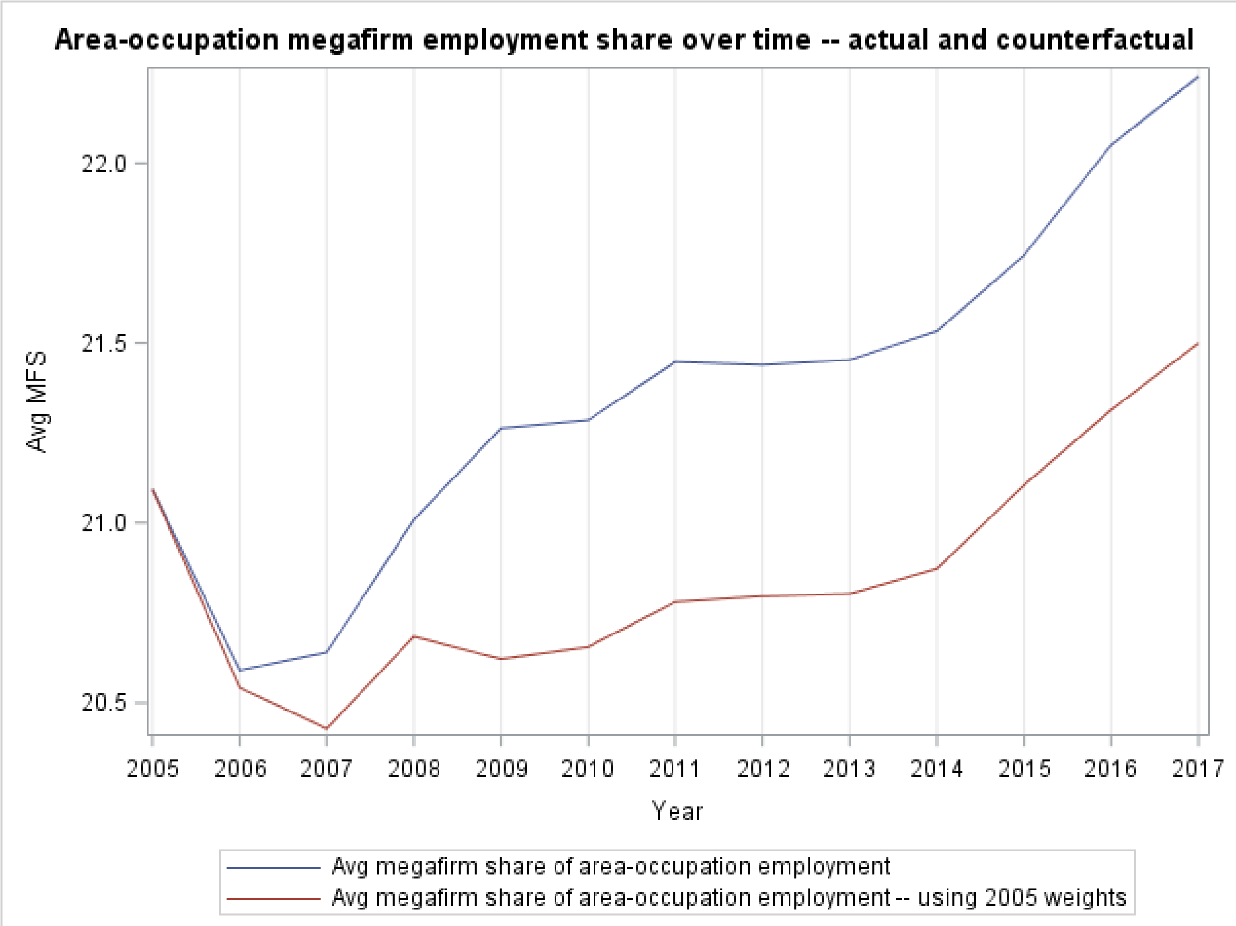
Figure 5: Trends in Measures of Employer Power at the Area x Occupation and Area x Industry Level, 2005-2017



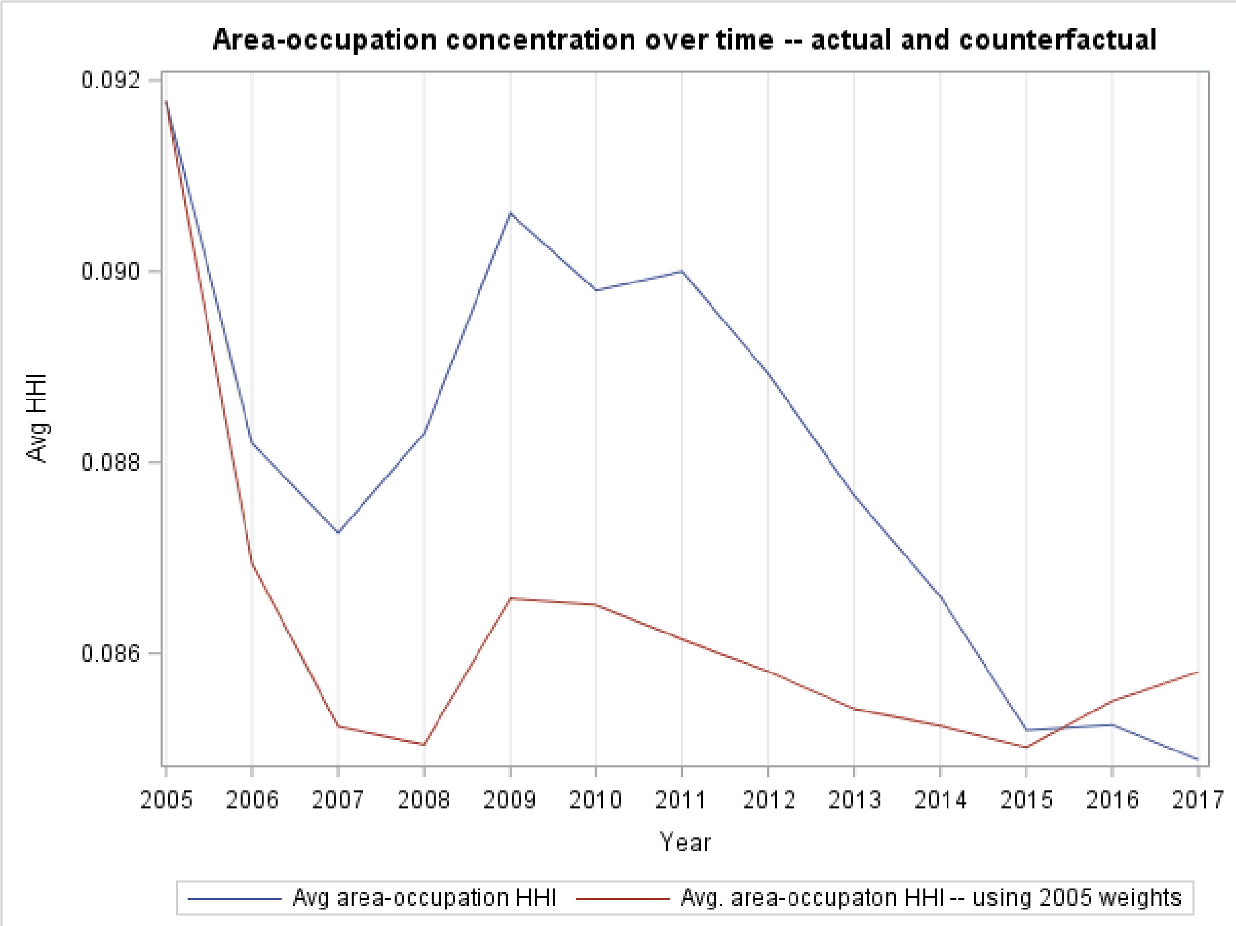
Notes: This figure shows trends in the average share of each Metropolitan/Balance-of-State area x 4-digit NAICS industry combination employed in "Megafirms": EINS with employment of 10,000 or more, over time in the QCEW data. The red line gives this fraction, holding the level of employment in each area x industry combination fixed at its 2005 levels.



Notes: This figure shows trends in the average Employer Concentration Level—as measured by the Herfindahl-Hirschman Index of payroll for each Metropolitan/Balance-of-State area x 4-digit NAICS industry combination over time in the OES data mapped onto QCEW data. The red line gives this fraction, holding the level of employment in each area x industry combination fixed at its 2005 levels.



Notes: This figure shows trends in the average share of each Metropolitan/Balance-of-State area x 6-digit occupation combination employed in "Megafirms": EINS with employment of 10,000 or more, over time in the QCEW data. The red line gives this fraction, holding the level of employment in each area x occupation combination fixed at its 2005 levels.



Notes: This figure shows trends in the average Employer Concentration Level—as measured by the Herfindahl-Hirschman Index of payroll for each Metropolitan/ Balance-of-State area x 6-digit occupation combination over time in the OES data mapped onto QCEW data. The red line gives this fraction, holding the level of employment in each area x occupation combination fixed at its 2005 levels.