Very Preliminary and Incomplete version of December, 2019

Variation in the impact of Explicit Oligopsony by Occupation

Elizabeth Weber Handwerker and Matthew Dey, U.S. Bureau of Labor Statistics

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 estimate employer labor market power by occupation for nearly all workers in the United States, in all sectors, all occupations, and all geographic areas, from 2005 to 2017. We document wide variation in the extent and wage impact of explicit oligopsony by occupation. We further document how much of this variation can be explained by various occupational characteristics.

Introduction

Slow U.S. wage growth during a lengthy economic expansion, combined with the increased availability of employer data for the U.S,, has sparked a rapidly growing literature examining the relationship between explicit oligopsony power and worker compensation in the U.S. Overall, this literature finds that there are many labor markets—especially in areas with small population—in which explicit oligopsony power is substantial. Furthermore, there is a negative relationship between the oligopsony power of employers in a market and the wages of workers in that market. However, this overall relationship belies wide variation among occupations in the extent of employer power and its wage impacts.

The literature linking explicit employer oligopsony power with worker compensation now includes papers such as Benmelech et al (2019), who show that employer concentration at the county-industry level has 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. 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. Schubert, Stansbury, and Taska (2019) show that the relationship between employer concentration and wages is driven by occupations and local geographic areas in which workers have the fewest outside options. Meanwhile, 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 explicit oligopsony, using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each local labor market. We define local labor markets as detailed occupations within each geographic area, following Azar et al., Schubert, Stansbury, and Taska, and Sojourner & Qiu, We construct this measure for all occupations, industries, and geographic areas of the United States—for the private sector only and for all employment. Using the same data, we also measure wages for each occupation within each establishment in the U.S. Borrowing aggregate skills and tasks that describe occupations from Dey & Loewenstein (2019) and measures of outside options by occupation from Schubert, Stansbury, and Taska (2019), we examine which characteristics of occupations are associated with the extent and impact of employer oligopsony.

We document the tremendous variation in the average level of employer concentration between occupations. Overall, small occupations have greater levels of employer concentration, but several other characteristics of occupations, including the outside options of workers and the average level of cognitive skill requirements of the occupation, are also associated with greater levels of oligopsony in local labor markets for occupations. We also show that the relationship between concentration and wages varies across occupations in ways that are consistent across different specifications. Certain occupations always have stronger associations between employer oligopsony power and wages than other occupations. Occupations that score highly in decision making tasks, in particular, have especially strong negative associations between employer power and wages, across all specifications. We also replicate Schubert, Stansbury, and Taska's conclusion that occupations with more outside options have lower associations between employer concentration and wages than occupations with fewer outside options. However, we can explain much more variation among occupations in the relationship between occupational concentration and wages once we add in other occupational characteristics.

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 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

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

result of the DPM approach is a census of employers that includes employment levels and wages by detailed occupation.[2]

We estimate the concentration of employers for each market, defined by geography and occupation. Geographically, we define markets as 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 also make numerous small adjustments and aggregations of occupation and industry definitions to make these consistent from 2005 to 2017. More substantially, we aggregate together all 41 occupations that the O*Net database describes as having *no entry requirements.* These include such occupations as fast food workers, cashiers, plasterers, meat trimmers, rock splitters, and taxi drivers. We define an employer as a collection of establishments within a market that share a common EIN in the QCEW data. We recognize the limitations of these data: there is ample evidence that EINs are not perfect measures of firms in these 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).

Let us define the set of employers as Ω. Following Azar et al and Qui & Sojourner 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. It differs from Qui & Sojourner in estimating this measure directly

[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.

from the occupational composition of employers rather than inferring occupational composition from their industries, as well as in estimating this measure for payroll, rather than for employment.

The average value of this measure is 0.069. 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,[4] which is lower than the 0.1638, weighted by employment in Azar et al (2018) or the ___ of Qui and Sojourner. 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.

In examining variation by occupation, we also bring in measures of occupational characteristics. These come from two sources:

(1) Dey and Lowenstein use factor analysis to condense the dozens of O*NET work activity variables into scores for each occupation for six aggregate skills and seven aggregate job tasks. The six skills are Speaking and listening skills, Sensory skills, Cognitive skills, Physical strength, Manual dexterity, and Math and reasoning skills. The seven job tasks are Working outdoors, Supervisory tasks, Analytical tasks, Physical tasks, Interacting with the public, Work with machines, and Decision making.
(2) Schubert, Stansbury, and Taska use online resume data to estimate the probability that a worker in each occupation will move from their occupation and location to another occupation or another location for their next job. They find that this measure of outside options has a substantial impact on the relationship between employer concentration and wages, and they have generously shared their index of outside options with us.

Heterogeneity by occupation in the extent of Employer Concentration

In this section, we show how average levels of employer concentration vary between occupations. Figure 1 shows that much of this variation is simply due to occupation size. The greater the employment level in an occupation nation-wide, the less the employer concentration in that occupation. This echoes the relationship between employer concentration and area employment first documented by Rinz (2018) and Azar et al (2019), and could arise from production processes that involve aggregations of workers, even in small occupations.

Nonetheless, Figure 1 shows that even among very large occupations, there is still considerable variation in average employer concentration levels. General Managers, Sales Representatives, and Bookkeeping Clerks have average HHI levels that average below 0.01, while Teacher Assistants, Team Assemblers, and

[4] These numbers come from old versions of the paper in which we didn't aggregate the 41 entry-level occupations. We need to update them.

Elementary School Teachers have average HHI levels above 0.10. Postal service occupations[5] (perhaps unsurprisingly) have among the highest average HHI levels (above 0.93), Air Traffic Controllers have average HHI levels of 0.92, graduate teaching assistants have average HHI levels of 0.82, and many scientific occupations also have high average HHI levels.

To move beyond lists of occupations, we perform simple regressions of HHI levels by year on Dey and Lowenstein's occupational skill and task scores, Schubert, Stansbury, and Taska's occupational mobility measure, national average wages for each occupation, and broad categories of occupational size (we do not use continuous size in the regressions, because they are weighted by occupation size)

The results of these regressions are in Table 2. These variables explain 42% of the variation in average HHI levels overall, and 53% of the variation in the private sector. There is little relationship between the average wage level of an occupation and the employer concentration of that occupation, and a negative relationship between the trend in wages for an occupation and its employer concentration. The largest coefficient is for Schubert, Stansbury, and Taska's occupational mobility measure: increasing the probability that workers leave an occupation-area market from 0 to 1 is associated with an increase in the average HHI of that occupation by 0.28. Within the private sector, the second largest coefficient is for Speaking and Listening skills: an increase in the cognitive skill score of an occupation by 1 standard deviation is associated with an increase in the average HHI of that occupation of 0.02. The smallest coefficients (aside from the coefficient on occupation size and wage trends) are for occupations involving decision-making. The occupations involving these tasks have lower HHI measures of employer concentration than other occupations.

Heterogeneity by occupation in Employer Concentration trends

Overall, the average employer concentration level of occupation-area markets declined slightly during this period, but patterns diverge greatly by occupation. Of the 745 occupations in our data (treating the 41 occupations with no entry-level requirements as a single occupation), 364 occupations, representing 43% of employment, have increasing concentration overall. Within the private sector, 385 occupations, representing 46% of employment, have increasing concentration overall.[6]

As examples, Figure 2 displays selected large occupations with very different trends in average HHI levels over time. These different trends are likely driven by differing forces in the labor market. Correctional Officers and Jailers as well as First line Supervisors of Police and Detectives are examples of several police occupations with falling concentration levels, both in the private sector and overall. We think this could arise from increased contracting out of some of these positions from local governments to a greater number of private-sector employers, although we note the increasing concentration of Detectives and Criminal Investigators. In contrast, Machine Feeders and Offbearers have some of the largest increases in employer concentration. This may be due to reduced operations or closures for

Postmasters and Mail Superintendents; Postal Service Clerks; Postal Service Mail Carriers; and Postal Service Mail Sorters, Processors, and Processing Machine Operators

[6] There are 5 occupations that appear in the OES data only in the public sector: Legislators; Fish and Game Wardens; Administrative Law Judges, Adjudicators, and Hearing Officers; Tax Examiners and Collectors, and Revenue Agents; and Judges, Magistrate Judges, and Magistrates

many employers of this industrial occupation during this period. Personal Care Aides also have large increases in employer concentration, but this may be due to mergers in the health sector. Some other occupations may also be spuriously measured as having declining employer concentration in the OES data: there is declining concentration for many of the largest "All other" residual occupation categories,[7] and some of the decline may be attributable to OES field staff working with large employers to assign more precise occupation codes to more of their employees.

To examine overall patterns in these trends by occupation, we regress concentration levels in each occupation on year to estimate a linear time trend for each occupation. Then, we perform simple regressions of the resulting trends on Dey and Lowenstein's occupational skill and task scores and Schubert, Stansbury, and Taska's occupational mobility measure, again weighting the regressions by occupation size and including the average nation-wide wage.

Results of these regressions are in Table 3. Occupational characteristics can explain only about 10% of the variation in employment concentration trends between occupations. Occupations with rising wages have rising levels of occupational concentration. Occupations involving working outdoors, physical tasks, and work with machines have the greatest increases in employer concentration. This is consistent with greater employer concentration for the surviving employers in the industrial sector. Occupations involving manual dexterity, decision making, sensory skills, and interacting with the public have the greatest declines in employer concentration. Schubert, Stansbury, and Taska's occupational mobility measure does not have a significant relationship with trends in employer concentration, after controlling for other occupational characteristics. The impact of wage levels is significant but insubstantial.

Heterogeneity by occupation in the wage impact of Employer Concentration

Among the central motivations for the existing literature on employer concentration in the labor market has been the potential impact of employer concentration on wages. This literature has focused on the overall impact of employer concentration on wages, generally using instrumental variables approaches to avoid confounding the true relationship between concentration and wages with local demand shocks. To our knowledge, the only paper before us that examines any kind of heterogeneity among occupations in the impact of employer concentration on wages has been Schubert, Stansbury, and Taska, who focus on the permeability of labor markets.

Rinz (2018), Azar et al (2019), and Qiu and Sojourner (2019) use leave-one-area-out instruments for the average concentration of a market (industry x area for Rinz, occupation x area for the others). This instrument has minimal variation across areas for each occupation (or industry, in the case of Rinz), and essentially uses the overall occupation (or industry, in the case of Rinz) composition of an area as a proxy for its employment concentration. Thus, we cannot use this instrument to estimate how the relationship between employment concentration and wages varies between occupations. However, the richness of our data allows us to construct a similar instrument that has more variability within

[7] These are the SOC codes ending in '98' and '99,' such as 33-9099: Protective Service Workers, All Other; 21-1798: Community and Social Service Specialists, All Other; 25-9099:Education, Training, and Library Workers, All Other; 29-2799: Health Technologists and Technicians, All Other; 15-1799: Computer Occupations, All Other; 43-4199: Information and Record Clerks, All Other; and 51-9399: Production Workers, All Other

occupations. This instrument allows two stage least squares estimation of the relationship between labor market concentration and wages separately for each occupation.

We construct the same leave-one-area-out instrument as other authors for each occupation, across all areas and industries, to compare our work with theirs. We then construct a second instrument, using the size of an area and its industrial composition in addition to its occupational distribution. For each area-occupation-industry combination, we calculate a leave-one-area out average of employment concentration among areas of similar size that contain the same industry. To form areas of similar size, we divide MSAs into deciles by overall employment size, and rural areas into quartiles by overall employment size. Thus, for example, for nurses working in hospitals in the largest decile of MSAs, we instrument employer concentration with the leave-one-area-out average of employment concentration for all nurses in other MSAs in the largest decile containing hospitals, while for nurses working in mines in small rural areas, we instrument employer concentration with the leave-one-area-out average of employment concentration for all nurses in other small rural areas containing mines. This second instrument has much more variation within occupations.[8]

As shown in Table 4, the correlation between estimated HHI for markets defined by area and occupation and the leave-one-area-out instrument used by Azar et al, Qiu & Sojourner, or Rinz is 0.65, while the correlation between estimated HHI and our preferred instrument is 0.75.

Table 5 shows overall results of regressing hourly ln(wage) on the log of employer concentration in occupation x area labor markets. These are equations of the form:

$$(1)\quad \ln(wage)_{isjgt} = \beta_0 + \boldsymbol{\beta_1}\, \boldsymbol{ln}(\boldsymbol{HHI_{jg}}) + \beta_3\, size_e + \textstyle\sum_j \beta_{4j}\, I(j) + \sum_s \beta_{5t}\, I(s) + \sum_g \beta_{6g}\, I(g) + \sum_t \beta_{7t}\, I(t) + \varepsilon_{ijgt}$$

Column (1) shows OLS regression coefficients of directly measured employer concentration, controlling for employer size, occupation$j$, year t, industry s, and MSA g.

The resulting estimate for the coefficient of interest, β_1, is 0.005 in the private sector, and 0.004 overall. This estimate is comparable to the estimates in Table 2A of Qiu & Sojourner, which range from 0.003 to 0.006. In column (2), we instead use the overall leave-one-out instrument that Azar and Qui & Sojourner use, again controlling for employer size, occupation, year, and industry x MSA. The resulting estimate is -0.005 in the private sector and -0.004 overall. This estimate is smaller than the estimates in Table 3A of Qiu & Sojourner, which range from -0.209 to -0.279. In column (3), we use our preferred instrument, described above, with the same controls. The resulting estimate is -.001 in the private sector and 0.009 overall.

We doubt that the positive sign of this wage coefficient (driven by observations in the government sectors) will be among the main conclusions of this paper, when it is more complete, because the sign of this wage coefficient is sensitive to the estimation strategy chosen. In column (4) of Table 5, we show the results of a OLS regression of directly measured logged employer concentration on hourly ln(wage),

[8] This second instrument also has variation within occupations in the same labor market. For the example of nurses in a small rural area, the actual employer concentration for all nurses in the market will be the same. However, the nurses who work in a hospital in that market will have a different instrument for employer concentration than the nurse who works for a mine.

controlling for employer size, occupation, year, and **establishment fixed effects**. Here the coefficient is negative, with a value of -0.039 in the private sector. We hope to run regressions using our preferred instrument and establishment fixed effects, but we have not been able to run these regressions yet.[9]

Rather, this is a paper about heterogeneity by occupation. We continue by taking the wage regressions of Table 5 (except those of column 2) and replacing the employer concentration variables with interactions between employer concentration and individual occupations. Thus we have equations of the form:

$$(2)\quad \ln(wage)_{ijgt} = \beta_0 + \boldsymbol{\beta_{1j} I(j)} * \mathbf{ln}(\boldsymbol{HHI_{jg}}) + \beta_3\, size_e + \sum_j \beta_{4j}\, I(j) + \sum_s \beta_{5s}\, I(s) + \sum_g \beta_{6g}\, I(g) + \sum_t \beta_{7t}\, I(t) + \varepsilon_{ijgt}$$

The resulting β_{1j} coefficients are occupation-specific estimates of the impact of employer concentration on wages.

There are many occupations that have consistently high or consistently low wage coefficients on employer concentration, across all specifications. Whether Employer Concentration is directly measured or instrumented, whether in the private sector or overall, and whether we use fixed effects for industries and geographic areas or fixed effects for establishments, these occupations see consistently higher or consistently lower wage coefficients for employer concentration. Pharmacists, Automotive and Watercraft Service Attendants, Gaming Dealers, and Home Health Aides all consistently show among the highest wage coefficients for employer concentration. General and Operations Managers, Real Estate Sales Agents, Carpenters, and Financial Managers all consistently show among the lowest wage coefficients for employer concentration. More generally, there is a correlation of about 0.8 between the wage coefficient interactions of the two OLS regressions, and a correlation of about 0.7 between the wage coefficient interactions from the first OLS regression and the wage coefficients interactions for the same occupations in the 2SLS regressions for the private sector. We turn to the same measures of occupation characteristics as above to look for patterns in wage coefficient interactions.

Table 6 gives the result of simple regressions of the occupation-specific OLS wage coefficients on Employer Concentration (with NAICS x MSA fixed effects) on Dey and Lowenstein's occupational skill and task scores, Schubert, Stansbury, and Taska's occupational mobility measure, and the average nation-wide wage for each occupation. The wage coefficients here are occupation-interactions of the overall coefficient in column (1) of Table 5. Occupational characteristics can explain about 27% of the variation in these occupation-specific OLS wage interactions for the private sector. Wage-level coefficients are small and not significant, while wage-trend coefficients are not significant in the private sector. The largest coefficients (in the private sector) are those on Schubert, Stansbury, and Taska's occupational mobility measure. The largest significantly positive coefficients those on physical tasks and cognitive skills, while the largest significantly negative coefficients are those on Decision making tasks.

---

[9] Because of the size of our data and the capabilities of our computers, we have been unable to run these regressions in Stata without restricting the data to one small state. We are able to run 2SLS regressions in SAS with a limited number of fixed effects, but SAS allows less than 38,000 fixed effects, and our 2SLS procedure requires using an output statement in PROC GLM, which prevents us from using an ABSORB statement in the same procedure call. If you know how to run 2SLS or IV regressions with high dimensional fixed effects in SAS…we really want to talk to you.

Table 7 gives the result of repeating this exercise, but explaining the occupation-specific wage coefficients from the 2SLS regressions that use our preferred instrument for Employer Concentration. The wage coefficients here are occupation-interactions of the overall coefficient in column (3) of Table 5. Occupational characteristics can explain 33-46% of the variation in these occupation-specific wage interactions. In these regressions, Schubert, Stansbury, and Taska's occupational mobility measure has the largest positive coefficient, and it is always significant. The largest significantly positive other coefficients (in the private-sector) are those on Physical tasks, while the largest significantly negative coefficients are those on Decision making and supervisory tasks.

Table 8 again repeats this exercise, for the occupation-specific OLS wage coefficients on Employer Concentration (here with establishment fixed effects). The wage coefficients here are occupation-interactions of the overall coefficient in column (4) of Table 5. Occupational characteristics can explain 15 – 32% of the variation in these occupation-specific OLS wage interactions. Wage-level coefficients continue to be very small, and the largest coefficients are again those on Schubert, Stansbury, and Taska's occupational mobility measure. The largest significantly positive other coefficients are again those on Physical tasks, while the largest significantly negative coefficients are again those on Decision making and supervisory tasks.

The consensus of the literature is that overall, employer concentration is associated with lower wages for workers. We are able to replicate this relationship in both 2SLS specifications and when we include employer fixed effects in OLS wage regressions, in columns (2-4) of Table 5, with occupation-interactions studied in Tables 7 and 8. We replicate Schubert, Stansbury, and Taska's conclusion that occupations with a lower probability of leaving have lower wage coefficients on employer concentration than occupations with a higher probability of leaving. However, as shown in Tables 7 and 8, this variable explains much less of the heterogeneity between occupations in the relationship between occupational concentration and wages than the collection of other occupational attributes identified by Dey & Lowenstein.

Conclusion

Using new methods to map the detailed occupation and wage distribution microdata of the Occupational Employment Statistics onto the employment patterns of nearly every establishment in the United States for 2005-2017, we study heterogeneity between occupations in the extent of explicit employer oligopsony power, its trends, and the relationship between employer power and wages.

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 Schubert, Stansbury, and Taska did not identify the only occupational characteristic that matters in explaining the relationship between employer concentration and wages.

References

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2017). The fall of the labor share and the rise of superstar firms. No. w23396. National Bureau of Economic Research.

Azar, José, Ioana Marinescu, and Marshall I. Steinbaum. (2019a) *Labor Market Concentration*. No. w24147. National Bureau of Economic Research.

Azar, José, Ioana Marinescu, and Marshall I. Steinbaum. (2019b) *Measuring Labor Market Power Two Ways*. AEA Papers and Proceedings 109, 317-21

Azar, José, Ioana Marinescu, Marshall I. Steinbaum, and Bledi Taska. (2018) "Concentration in US Labor Markets: Evidence From Online Vacancy Data." No. w24395 National Bureau of Economic Research.

Benmelech, E., Bergman, N., & Kim, H. (2019). "Strong Employers and Weak Employees: How Does Employer Concentration Affect Wages?" (No. w24307). National Bureau of Economic Research.

Berger, David, Kyle Herkenhoff, & Simon Mongey. (2019) "Labor Market Power." (No. w25719) National Bureau of Economic Research

Cardiff-Hicks, B., Lafontaine, F., & Shaw, K. (2015). Do Large Modern Retailers Pay Premium Wages?. ILR Review, 68(3), 633-665.

Dey, Matthew, and Mark Loewenstein (2019). "On Job Requirements, Skill, and Wages". BLS Working Paper 513, https://www.bls.gov/osmr/research-papers/2019/ec190030.htm

Dey, Matthew, David Piccone, and Stephen Miller (2019?). Model-based Estimates for the Occupational Employment Statistics Program. *Monthly Labor Review*, U.S. Bureau of Labor Statistics, forthcoming

Foote, Andrew, Mark Kutzbach, and Lars Vilhuber (2017). "Recalculating ... : How Uncertainty in Local Labor Market Definitions Affects Empirical Findings." Center for Economic Studies Working Paper CES 17-49, https://www2.census.gov/ces/wp/2017/CES-WP-17-49.pdf

Handwerker, Elizabeth Weber, & Mason, Lowell G. (2013). Linking firms with establishments in BLS microdata. *Monthly Labor Review*, Vol 136, No 14.

Hershbein, Brad, Claudia Macaluso, & Chen Yeh (2019). "Concentration in U.S. local labor markets: Evidence from vacancy and employment data." Working paper at https://drive.google.com/open?id=1yd8jyQANpImD1bGChFn9iQF0pe3boYck

Lipsius, Ben (2018). "Labor Market Concentration Does Not Explain the Falling Labor Share." Working Paper at https://drive.google.com/open?id=1VKgdb2U5llYzSbmfqF46kW3TGqluELrZ

Prager, Elena, and Matt Schmitt. "Employer Consolidation and Wages: Evidence from Hospitals" Working paper at https://www.anderson.ucla.edu/documents/areas/fac/policy/Schmitt/PragerSchmitt_MergersAndWages_19.05.07.pdf

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, & Nicholas Trachter (2018). "Diverging Trends in National and Local Concentration" (No. 25066) National Bureau of Economic Research.

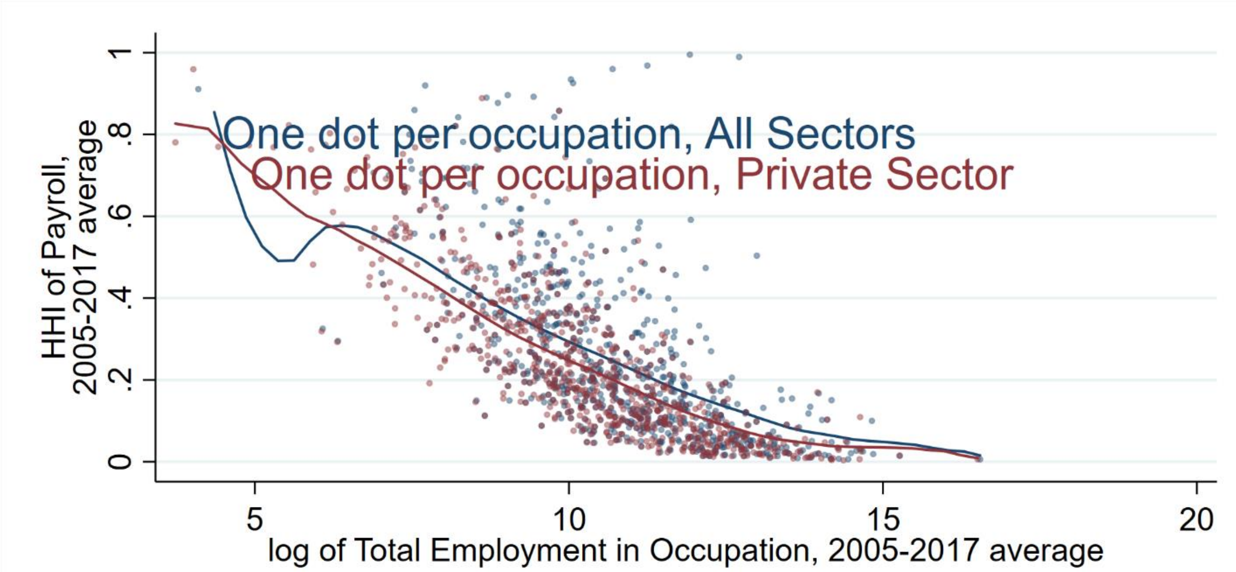
Rinz, Kevin. (2018). "Labor Market Concentration, Earnings Inequality, and Earnings Mobility." CARRA Working Paper 2018-10, https://www.census.gov/content/dam/Census/library/working-papers/2018/adrm/carra-wp-2018-10.pdf

Schubert, Gregor, Anna Stansbury, and Bledi Taska. (2019). "Mitigating Monopsony: Occupational Mobility and Outside Options" https://scholar.harvard.edu/files/stansbury/files/schubert-stansbury-taska-20191106.pdf

Qiu, Que, and Aaron Sojourner. (2019). Labor-Market Concentration and Labor Compensation Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3312197

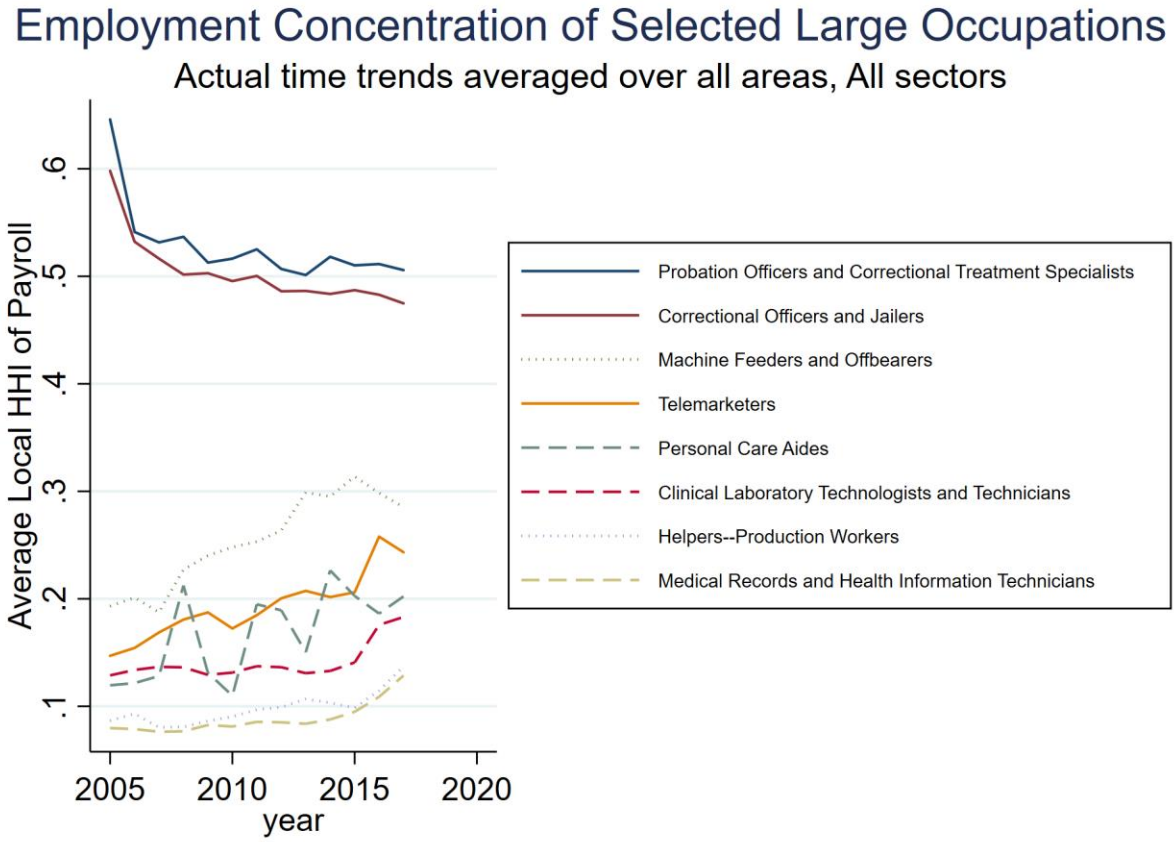
James Spletzer and Elizabeth Handwerker. (2014). Measuring the distribution of wages in the United States from 1996 through 2010 using the Occupational Employment Survey. *Monthly Labor Review*, U.S. Bureau of Labor Statistics

Figure 1: Average Employer Concentration by Occupation Size



Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area). It is calculated for all sectors and for the private sector only. Each dot in this figure is an employment-weighted average of concentration across all geographic areas, then a simple average across all years. 41 occupations with no entry requirements are combined into a single occupation. Each line is an lpoly. The data is the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States.

Figure 2: Trends in Employer Concentration for Selected Large Occupations



Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area). It is calculated for all sectors and for the private sector only. Each line in this figure is an employment-weighted average of concentration across all geographic areas. The data is the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States.

Table 1: Summary Statistics (weighted by employment)

Variable	N	Mean	Std Dev	Minimum	Maximum
NAICS	129,432,097	N/A	N/A	113310	813990
Ownership code	129,432,097	N/A	N/A	1	5
MSA or Balance of State Area	129,432,097	N/A	N/A	10180	5600004
Employment per EIN	129,432,097	34,825.87	42,8863.5	1	confidential
HHI of payroll for area x occupation	129,432,097	0.068598	0.303842	0.00019	1
Leave-one-out estimator of HHI, across all areas and industries	129,432,097	0.07492	0.222126	0.004804	1
Leave-one-out estimator of HHI, restricted to areas of similar size containing the same industry	129,432,097	0.067658	0.253477	0.000235	1
Private-sector HHI of payroll	129,432,097	0.069292	0.317037	0.00019	1
Private-sector leave-one-out estimator of HHI across all	129,432,097	0.069914	0.201225	0.00289	1
Private-sector leave-one-out estimator of HHI, restricted	129,432,096	0.066432	0.252196	0.000238	1
Lnwage, $2000	129,432,097	2.5811505	1.276867	1.1958671	5.1338004

Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area) in each year from 2005-2017. 41 occupations with no entry requirements are combined into one occupation. The leave-one-out estimator across all areas and industries simply averages the HHI Index for the same occupation in all other geographic areas. The leave-one-out estimator restricted to areas of similar size containing the same industry averages the HHI Index for the same occupation in areas of the same area type (MSA vs. rural), area size, and that contain the same industry as the original observation. The data is the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005, 2008, 2011, 2014, and 2017. Observations are at the employer x occupation x year level, weighted by employment in each cell.

Table 2: Correlates between Employer Concentration **levels** and Occupation Characteristics

	All sectors	All sectors	Prvt sector	Prvt sector
Probability_of_leaving	-0.191***	0.138***	-0.039**	0.141***
Wage_level		0.003***		0.001***
Wage_trend		-0.091***		-0.018***
Working_outdoors		0.006*		-0.003*
Supervisory_tasks		-0.038***		-0.014***
Analytical_tasks		-0.014***		0.000
Physical_tasks		0.030***		0.015***
Interacting_with_the_public		-0.007***		-0.017***
Work_with_machines		0.017***		0.012***
Decision_making		-0.048***		-0.023***
Speaking_and_listening_skills		0.021***		0.023***
Sensory_skills		0.004		0.005**
Cognitive_skills		0.054***		0.018***
Physical_strength		-0.024***		-0.008***
Manual_dexterity		-0.032***		-0.010***
Math_and_reasoning_skills		-0.009***		-0.009***
Occupation_size_category		-0.081***		-0.065***
Constant	0.130***	0.601***	0.072***	0.488***
R-squared	0.008	0.419	0.001	0.534
N	9589	9589	9537	9537

* p<0.05, ** p<0.01, *** p<0.001

Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area) in each year from 2005-2017. 41 occupations with no entry requirements are combined into one occupation. Employer Concentration data comes from the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005-2017. Average concentration levels and average wage levels for each occupation in each year are combined with occupation level skills and tasks from Dey & Loewenstein and with the probability of leaving that occupation for another occupation in the same area or the same occupation in a different area from Schubert, Stansbury, & Taska. This is a table of regressions of the form: $\text{Average\_Employer\_Concentration}_o = \alpha + \text{occupation\_characteristics}_o + \varepsilon_o$, with observations at the occupation x year level, weighted by occupation size in that year.

Table 3: Correlates between Employer Concentration **trends** and Occupation Characteristics

	All sectors	All sectors	Prvt sector	Prvt sector
Probability_of_leaving	0.0047**	-0.0012	0.0038*	-0.0001
Wage_level		0.0000		0.0000
Wage_trend		0.0014*		0.0013*
Working_outdoors		0.0009***		0.0007**
Supervisory_tasks		-0.0003		-0.0004*
Analytical_tasks		0.0003		0.0005*
Physical_tasks		0.0007**		0.0006**
Interacting_with_the_public		-0.0006**		-0.0006***
Work_with_machines		0.0010***		0.0008***
Decision_making		-0.0008***		-0.0008***
Speaking_and_listening_skills		0.0004		0.0006**
Sensory_skills		-0.0009***		-0.0007**
Cognitive_skills		-0.0006*		-0.0006*
Physical_strength		-0.0000		0.0002
Manual_dexterity		-0.0008***		-0.0008***
Math_and_reasoning_skills		0.0004*		0.0003
Occupation_size_category		-0.0002		-0.0003*
Constant	-0.0013**	0.0008	-0.0008*	0.0016
R-squared	0.009	0.093	0.007	0.101
N	738	738	734	734

* p<0.05, ** p<0.01, *** p<0.001

Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area) in each year from 2005-2017. 41 occupations with no entry requirements are combined into one occupation. Employer Concentration data comes from the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005-2017. Linear time trends in occupational concentration and average wage levels for each occupation across all years are combined with occupation level skills and tasks from Dey & Loewenstein and with the probability of leaving that occupation for another occupation in the same area or the same occupation in a different area from Schubert, Stansbury, & Taska. This is a table of regressions of the form: $\text{Employer\_Concentration\_Trend}_o = \alpha + \text{occupation\_characteristics}_o + \varepsilon_o$, with observations at the occupation level, weighted by average occupation sizes across all years.

Table 4: Raw Correlations between Estimates of Employer Concentration and Instruments based on Employer Concentration in other geographic areas

	All observations	Private-sector only
Leave-one-out estimator, across all areas and industries	0.65460 (0.00953)	0.59949 (0.00671)
Leave-one-out estimator, restricted to areas of similar size containing the same industry	0.75434 (0.01253)	0.72292 (0.01025)
Observations	129,432,097	125,556,272

Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area). 41 occupations with no entry requirements are combined into one occupation. The leave-one-out estimator across all areas and industries simply averages the HHI Index for the same occupation in all other geographic areas. The leave-one-out estimator restricted to areas of similar size containing the same industry averages the HHI Index for the same occupation in areas of the same area type (MSA vs. rural), area size, and that contain the same industry as the original observation. The data is the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005, 2008, 2011, 2014, and 2017. Observations are at the employer x occupation x year level, weighted by employment in each cell.

Table 5: Relationship between Employer Concentration and hourly wages across all occupations in OLS and 2SLS regressions

	Panel A: All observations			
	(1)	(2)	(3)	(4)
OLS regressions	0.004228			-0.035081
	(0.000042)			(0.000032)
2SLS regression with the leave-one-out instrument		-0.003502		
		(0.000592)		
2SLS regression with our preferred instrument			0.009111	
			(0.000179)	
Employer EIN size	Y	Y	Y	Y
Occupation and Year FE	Y	Y	Y	Y
Establishment Industry x MSA FE	Y	Y	Y	
Establishment FE				Y
R^2	0.777291	0.777274	0.777278	0.801460
N	129,432,097	129,432,097	129,432,097	129,432,097
	Panel B: Private sector only			
	(1)	(2)	(3)	(4)
OLS regressions	0.004918			-0.038680
	(0.000045)			(0.000032)
2SLS regression with the leave-one-out instrument		-0.004789		
		(0.000427)		
2SLS regression with our preferred instrument			-0.001255	
			(0.000176)	
Employer EIN size	Y	Y	Y	Y
Occupation and Year FE	Y	Y	Y	Y
Establishment Industry x MSA FE	Y	Y	Y	
Establishment FE				Y
R^2	0.777051	0.777030	0.777029	0.801475
N	125,556,272	125,556,272	125,556,272	125,556,272

Notes: Employer Concentration is measured using the log of a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area). The 41 occupations with no entry requirements are considered as one occupation for the purposes of calculating employer concentration. The leave-one-out instrument simply averages the HHI Index for the same occupation in all other geographic areas. Our preferred instrument is a leave-one-out estimator restricted to areas of similar size containing the same industry, averaging the HHI Index for the same occupation in areas of the same area type (MSA vs. rural), area size, that contain the same industry as the original observation. The data is the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005, 2008, 2011, 2014, and 2017. Observations are at the employer x occupation x year level, weighted by employment in each cell (no wage variation within occupation x employer cells). Establishment Fixed effects are not quite right for most government observations. *The standard errors for the 2SLS regressions are wrong, because we're literally running two regressions. If you can tell us how to correctly do IV regression with fixed effects in SAS, we really want to talk to you. Especially if you can also tell us how to cluster our standard errors.*

Table 6: Correlates between **OLS estimates of the wage impact** of Employer Concentration (incorporating MSA x NAICS fixed effects) and Occupation Characteristics

	All sectors	All sectors	All sectors	Prvt sector	Prvt sector	Prvt sector
Probability_of_leaving	0.048		0.035	0.062***		0.040**
Wage_level		0.002***	0.002***		0.000	0.000
Wage_trend		-0.054***	-0.054***		-0.003	-0.003
Working_outdoors		0.012*	0.011*		0.005**	0.005*
Supervisory_tasks		-0.018***	-0.018***		-0.005***	-0.005***
Analytical_tasks		-0.005	-0.005		-0.002	-0.002
Physical_tasks		0.009*	0.010*		0.006***	0.006***
Interacting_with_the_public		0.003	0.004		0.000	0.001
Work_with_machines		0.014**	0.013**		0.006***	0.005**
Decision_making		-0.031***	-0.031***		-0.014***	-0.013***
Speaking_and_listening_skills		0.005	0.004		0.003	0.002
Sensory_skills		-0.014**	-0.013**		-0.006**	-0.005*
Cognitive_skills		0.016**	0.017**		0.005*	0.006**
Physical_strength		-0.002	-0.002		-0.003	-0.003
Manual_dexterity		-0.012**	-0.012*		-0.005**	-0.004*
Math_and_reasoning_skills		-0.000	-0.001		0.000	-0.000
Occupation_size_category		-0.007**	-0.007*		-0.002*	-0.002
Constant	-0.001	0.039	0.027	-0.007*	0.023**	0.010
R-squared	0.001	0.127	0.127	0.026	0.269	0.275
N	734	740	734	734	740	734

* p<0.05, ** p<0.01, *** p<0.001

Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area) in each year from 2005-2017. 41 occupations with no entry requirements are combined into one occupation. Employer Concentration data comes from the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005, 2008, 2011, 2014, and 2017. In the wage regression of employer concentration shown in **column (1)** of Table 5, occupation-level interactions replace the overall employer concentration level, to produce wage coefficients for each occupation. These coefficients are then combined with occupation level skills and tasks from Dey & Loewenstein and with the probability of leaving that occupation for another occupation in the same area or the same occupation in a different area from Schubert, Stansbury, & Taska. This is a table of regressions of the form: $\text{Wage\_coefficient}_o = \alpha + \text{occupation\_characteristics}_o + \varepsilon_o$, with observations at the occupation level, weighted by average occupation sizes across all years.

Table 7: Correlates between **2SLS estimates of the wage impact** of Employer Concentration (incorporating MSA and NAICS fixed effects) and Occupation Characteristics

	All sectors	All sectors	All sectors	Prvt sector	Prvt sector	Prvt sector
Probability_of_leaving	0.085***		0.068**	0.111***		0.088***
Wage_level		-0.001**	-0.001*		-0.000	0.000
Wage_trend		0.021**	0.019*		-0.001	-0.002
Working_outdoors		0.001	-0.000		0.004	0.002
Supervisory_tasks		-0.005**	-0.006**		-0.007***	-0.008***
Analytical_tasks		0.000	0.000		-0.002	-0.002
Physical_tasks		0.011***	0.012***		0.014***	0.014***
Interacting_with_the_public		0.003	0.004*		0.002	0.004*
Work_with_machines		0.002	-0.000		0.006**	0.004
Decision_making		-0.013***	-0.013***		-0.018***	-0.017***
Speaking_and_listening_skills		0.002	0.001		0.002	0.001
Sensory_skills		-0.006*	-0.004		-0.007**	-0.005*
Cognitive_skills		0.002	0.004		0.002	0.005
Physical_strength		-0.001	-0.002		-0.005	-0.006*
Manual_dexterity		0.001	0.002		-0.003	-0.001
Math_and_reasoning_skills		0.000	-0.000		0.001	0.000
Occupation_size_category		0.001	0.001		0.001	0.002
Constant	-0.005	0.016	-0.007	-0.024***	-0.007	-0.036***
R-squared	0.020	0.326	0.332	0.041	0.447	0.462
N	734	740	734	734	740	734

* p<0.05, ** p<0.01, *** p<0.001

Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area) in each year from 2005-2017. 41 occupations with no entry requirements are combined into one occupation. Employer Concentration data comes from the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005, 2008, 2011, 2014, and 2017. In the wage regression of employer concentration shown in **column (3)** of Table 5, occupation-level interactions replace the overall employer concentration level, to produce wage coefficients for each occupation. These coefficients are then combined with occupation level skills and tasks from Dey & Loewenstein and with the probability of leaving that occupation for another occupation in the same area or the same occupation in a different area from Schubert, Stansbury, & Taska. This is a table of regressions of the form: $\text{Wage\_coefficient}_o = \alpha + \text{occupation\_characteristics}_o + \varepsilon_o$, with observations at the occupation level, weighted by average occupation sizes across all years.

Table 8: Correlates between **OLS estimates of the wage impact** of Employer Concentration (incorporating establishment fixed effects) and Occupation Characteristics

	All sectors	All sectors	All sectors	Prvt sector	Prvt sector	Prvt sector
Probability_of_leaving	0.023		0.056*	0.039*		0.072***
Wage_level		0.000	0.001		0.000	0.000
Wage_trend		-0.005	-0.006		-0.002	-0.003
Working_outdoors		0.003	0.002		0.008***	0.007**
Supervisory_tasks		-0.009***	-0.009***		-0.006***	-0.006***
Analytical_tasks		0.009**	0.009**		0.008***	0.008***
Physical_tasks		0.007*	0.008**		0.011***	0.011***
Interacting_with_the_public		-0.009***	-0.008**		-0.006***	-0.005***
Work_with_machines		0.007*	0.005		0.003	0.001
Decision_making		-0.013***	-0.013***		-0.013***	-0.013***
Speaking_and_listening_skills		0.009**	0.008**		0.004*	0.003
Sensory_skills		-0.004	-0.003		-0.006**	-0.005*
Cognitive_skills		0.001	0.003		0.000	0.002
Physical_strength		0.002	0.002		-0.004	-0.004
Manual_dexterity		-0.006	-0.005		-0.003	-0.002
Math_and_reasoning_skills		-0.000	-0.001		0.001	0.001
Occupation_size_category		-0.007***	-0.007***		-0.004***	-0.004**
Constant	-0.036***	0.014	-0.005	-0.045***	-0.005	-0.029**
R-squared	0.000	0.145	0.149	0.006	0.307	0.323
N	734	740	734	734	740	734

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes: Employer Concentration is measured using a Herfindahl-Hirschman Index (HHI) of payroll by employer within each six-digit occupation for each geographic area (MSA or balance of state area) in each year from 2005-2017. 41 occupations with no entry requirements are combined into one occupation. Employer Concentration data comes from the microdata of the Occupational Employment Statistics, mapped to the full employment data of the Quarterly Census of Employment and Wages in the United States for 2005, 2008, 2011, 2014, and 2017. In the wage regression of employer concentration shown in **column (4)** of Table 5, occupation-level interactions replace the overall employer concentration level, to produce wage coefficients for each occupation. These coefficients are then combined with occupation level skills and tasks from Dey & Loewenstein and with the probability of leaving that occupation for another occupation in the same area or the same occupation in a different area from Schubert, Stansbury, & Taska. This is a table of regressions of the form: $\text{Wage\_coefficient}_o = \alpha + \text{occupation\_characteristics}_o + \varepsilon_o$, with observations at the occupation level, weighted by average occupation sizes across all years.