The Role of Establishments and the Concentration of Occupations in Wage Inequality

Elizabeth Weber Handwerker
James R. Spletzer

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Elizabeth Weber Handwerker
U.S. Bureau of Labor Statistics

James R. Spletzer
*U.S. Census Bureau
and IZA*

ABSTRACT

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This paper uses the microdata of the Occupational Employment Statistics (OES) Survey to assess the contribution of occupational concentration to wage inequality between establishments and its growth over time. We show that occupational concentration plays an important role in wage determination for workers, in a wide variety of occupations, and can explain some establishmentlevel wage variation. Occupational concentration is increasing during the 2000-2011 time period, although much of this change is explained by other observable establishment characteristics. Overall, occupational concentration can help explain a small amount of wage inequality growth between establishments during this time period.

JEL Classification: J31, D31, L11, D22, M12, M50

Keywords: wage inequality, establishments, occupational concentration, employers, employer-employee microdata

Corresponding author:

James R. Spletzer
Center for Economic Studies
U.S. Census Bureau
4600 Silver Hill Road
Washington, DC 20233
USA
E-mail: James.R.Spletzer@census.gov

I. Introduction

Growing inequality—of incomes, compensation, and wages—has been one of the dominant features of the US labor market over the last several decades. An enormous and growing literature has documented and attempted to explain this growing inequality and its many sources. A recent strand of the literature documents that much of the increasing inequality across workers is due to increasing inequality across employers – see, for example, Card, Heining, and Kline (2013); Barth, Bryson, Davis, and Freeman (2014); and Song, Price, Guvenen, Bloom, and von Wachter (2015). We build on this new strand of the literature in three ways: by bringing new U.S. linked employer-employee data to the inequality literature, by showing the importance of establishment effects in the widening distribution of wages, and by pursuing the hypothesis that the growing divergence of wages between establishments results from a changing distribution of occupations between workplaces.

An enormous literature has examined the composition and sources of growing inequality, using data on individual workers and their characteristics. This work has addressed the changing composition of the workforce and changing returns to education and experience (Bound and Johnson, 1992; Katz and Murphy, 1992; Lemieux, 2006), and the growing inequality within education and skill groups (Juhn, Murphy, and Pierce, 1993; Katz and Autor, 1999). Growing inequality has been attributed to many sources. These include the differential impact of technology on differing portions of the worker skill distribution, referred to as 'Skill Biased Technology Change' (Juhn, Murphy, and Pierce, 1993; Acemoglu, 2002; Autor, Katz, and Kearney 2008; and Autor and Dorn, 2013), changing labor market institutions such as declining unionization levels (Lemieux, 2008), the declining real value of the minimum wage (Card and DiNardo, 2002; Lee, 1999), and the growing fraction of workers subject to performance-based pay from their employers (Lemieux, MacLeod, and Parent, 2009). Although these explanations for growing inequality are concerned with the policies and incentives faced by employers, this literature uses worker microdata with little if any information on the businesses employing these workers.

A second, smaller literature has used employer data to study growing wage inequality from the perspective of businesses. This work builds on the evidence showing that establishments play an important role in determining individual wages (Groshen, 1991; Bronars and Famulari, 1997; Abowd, Kramarz, and Margolis, 1999; Lane, Salmon, and Spletzer, 2007). Several authors have used employer microdata to study growing variability in earnings in the U.S. from the mid-1970s to the early 2000s, and have found that the increasing variability is due more to variation between establishments than to variation within establishments (Davis and Haltiwanger, 1991; and Dunne, Foster, Haltiwanger, and Troske, 2004). This early literature has largely relied on combining measures of total variation in wages from worker microdata with measures of establishment mean wages from employer microdata. A new and growing literature, cited in the first paragraph above, uses matched employer-employee microdata to study inequality, and documents the importance of employers and the role of worker sorting between employers.

There is no clear explanation for why wage inequality between employers in the U.S. has been increasing. The forces that affect the overall distribution of wages—such as skill-biased technological changes, labor market institutions, and employer-specific pay policies—will have differential impacts on different employers. In addition, the wage distribution between employers will be affected by the sorting of workers among employers. While Card, Heining, and Kline (2013) find that increased assortativeness in the matching of highly-paid workers and higher-paying employers is an important part of increasing wage variability in West Germany, Barth, Bryson, Davis, and Freeman (2014) find that increased sorting of workers (by education) to establishments in the U.S has little impact on the overall divergence in pay between establishments in the U.S.

In this paper, we study another form of worker sorting between establishments: the concentration of occupations. Establishments may become more concentrated in occupations as the overall occupational distribution changes due to the replacement of certain routine occupations by technology (as discussed in Autor, Katz, and Kearney, 2008, and Autor and Dorn, 2013). Establishments may also become more concentrated in particular occupations as they contract out certain types of work in order to cut compensation costs, buffer their core work force from fluctuations in demand, and benefit from scale economies in specialty services (Abraham and Taylor, 1996).

To empirically examine whether the explanation for the large between-establishment effect in increasing inequality is due to changes in how establishments structure the occupational composition of their workforce, we use the microdata of the Occupational Employment Statistics (OES) Survey. The OES data is collected from a large annual survey of establishments, and contains information both on establishment characteristics and on the wage and occupational distributions of the employees within surveyed establishments. The OES data allow us to decompose increasing wage inequality in the U.S. into its within and between establishment components using a single source of wage information. These data also allow us to assess the impact of changing establishment characteristics (industry, size, and location) on the overall distribution of wages and in particular, on the between-establishment component of variation. In addition, OES data allow us to assess the contribution of the changing distribution of employment by occupation within establishments on the wage distribution.

This paper's main findings are fourfold. First, we confirm with the OES data that nearly all of the recent increase in wage inequality is between establishments rather than within establishments. Second, we show that the composition of occupations within establishments plays an important role in wage determination for workers, in a wide variety of occupations. Third, we show evidence of secular change in establishment-level occupational composition during the 2000-2011 time period, although much of this change can be fully explained by observable establishment characteristics. Fourth, we show that our measures of establishment-level occupational composition help explain growing wage inequality between establishments, but the estimated magnitude is small.

II. The Microdata of the Occupational Employment Statistics Survey

We use the microdata of the Occupational Employment Statistics (OES) Survey, conducted by the Bureau of Labor Statistics. This survey is designed to measure occupational employment and wages in the United States by geography and industry, and is the only such survey of its size and scope. The OES covers all establishments in the United States except for those in agriculture, private households, and unincorporated self-employed workers without employees. Every year, approximately 400,000 private and local government establishments are selected for this survey. They as asked to report the number of employees in each occupation paid within specific wage intervals.[1]

An abridged version of an OES survey form is shown in Figure 1. This survey form is a matrix, with occupations on the rows and wage intervals on the columns. For large establishments, the survey form lists 50 to 225 detailed occupations; these occupations pre-printed on the survey form are selected based on the industry and the size of the establishment. Small establishments receive a blank survey form and write in descriptions of the work done by their employees. These employer-provided descriptions are coded into occupations by staff in state labor agencies (as part of the OES Federal-State partnership). Many large employers also provide payroll data to BLS using their own job categories and titles, which are then coded into occupations by staff in state labor agencies. Wage intervals on the OES survey form are given in both hourly and annual nominal dollars, with annual earnings being 2080 times the hourly wage rates. To calculate average wages, the OES program obtains the mean of each wage interval every year from the National Compensation Survey (NCS). These mean wages are then assigned to all employees in that wage interval.

The OES cannot measure inequality in the top percentiles of the wage distribution. Earnings of individuals at the very top of the wage distribution are reported in an open-ended interval in the OES -- the uppermost interval in the recent OES surveys is "$166,400 and over" (the ranges of the intervals vary by year – see Handwerker and Spletzer (2014) for more information). Averaged across 1998 to May 2012, the uppermost interval contains roughly 1.3 percent of employment.

We impose only two restrictions on our OES data. First, we delete data collected from federal, state, and local governments, and second, we delete the 22% of the remaining establishments with imputed data. On average, we have data from roughly 275,000 establishments per year.

Two possible concerns about using OES data for studying inequality are the collection of wage data in intervals, and whether inequality measures in an establishment survey such as the OES mimic what we know from commonly used household surveys such as the Current

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[1] In the early years of our panel, the OES data were collected in October, November, and December. Starting in November 2002, data collection for 200,000 establishments occurs in November and data collection for 200,000 establishments occurs in May. The OES survey is not designed to produce time series statistics. We use the methodology described in Abraham and Spletzer (2010) to reweight the data to November or May benchmarks of total employment by detailed industry and by broad industry and establishment size groups from the Quarterly Census of Employment and Wages (QCEW). Abraham and Spletzer (2010) also describe how to create OES occupation and industry categories that are consistent over time.

Population Survey (CPS). In our earlier work (Handwerker & Spletzer, 2014), we compare wage data in the OES with wage data from the outgoing rotation groups of the CPS, and have two main findings. First, we show that the interval nature of wage collection in the OES has essentially no impact on measures of overall wage inequality trends. We show this by putting the CPS wage data through the filter of the OES wage intervals, demonstrating that the continuous CPS wage data and the intervalized CPS wage data show extremely similar wage inequality trends. Second, we show that the reweighted OES data can be used to broadly replicate basic CPS wage inequality trends, beginning in 1998. Overall wage distributions in each year are similar, as well as overall variance trends and variance trends by industry and occupation groups. In both the OES and the CPS, industry groups alone explain 15-17% of wage variation, although industry groups explain slightly more of the variation in the (employer-reported) OES than in the (employee-reported) CPS.

Our earlier work comparing wage inequality trends in CPS and OES microdata provides several reasons to focus on the importance of occupations and establishments for understanding inequality. We find that occupational groups alone explain more of the variation in wages in the OES (about 40%) than these same variables explain in the CPS (about 30%). This phenomenon was also noted by Abraham and Spletzer (2009), who attribute it to more accurate reporting of occupation by employers who answer the OES than by individuals who answer the CPS. We also find that the amount of wage variance explained by occupation is growing more quickly in the OES than in the CPS. Furthermore, we show that establishment effects, found in the OES but not the CPS data, explain more of wage variation than any other single variable in the OES.

III. The Role of Establishments

As highlighted in the introduction, many recent studies find that establishments (or firms) play an important role in determining wage inequality. Most comparable to our work is Barth, Bryson, Davis, and Freeman (2014), hereafter BBDF, who link together several large Census Bureau datasets (individual data from the CPS and Census, establishment data from the Longitudinal Business Database, and wage record data from nine states) to study the roles of employers and worker sorting between employers in wage inequality. They find major roles for industries and unexplained establishment effects in wage inequality and its growth, with smaller roles for geography and worker sorting. We compare several measures of wage inequality in the OES data to the findings of BBDF, before extending this work with measures of occupations and occupational concentration, which were not available to BBDF.

Figure 2 shows the decomposition of the total wage variance in the OES into its within-establishment and between establishment components. Over the period of Fall 1999 through November 2011, 55% of wage variance is between establishments, while 92% of the growth in overall wage variance from Fall 1999 to November 2011 is between establishments. BBDF estimate that 46-49% of variance in log earnings is between establishments, with 68% of variance growth during 1992-2007 between establishments.[2] Examining only employees who do

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[2] Other authors of related studies have focused on wages within manufacturing industries, and here also we find broadly consistent results. Davis and Haltiwanger (1991), find that 50 to 58 percent of wage variance in manufacturing is between plants, and 48 percent of variance growth in manufacturing is between plants. Dunne,

not change jobs, they find 79% of the growth in earning variance is between establishments. Although the OES data we use cover a different period than those used in BBDF, we find similar estimates of both the between-establishment component of wage variance and the growth of this component. Table 1 shows the decomposition by industry groups.

We follow BBDF in examining the factors that contribute to the average wage levels by establishment. Using data from November 2007, and letting subscript "j" index the establishment, we estimate the amount of establishment-level wage variance explained by the industry, geographic state, and size of establishments, using the regression equation

$$(1) \quad Ln(wage_j) = \alpha Industry_j + \beta State_j + \chi EstabSize_j + \varepsilon_j.$$

Results of this estimation are shown in the first two columns of Table 2. The first row of this table uses a set of 13 Broad Industry Groups,[3] and shows that using these groups alone, we can explain 18% of the variation in establishment-level wages—close to the 20% of establishment-level earnings variation that BBDF explain for 2007 using 1-digit industry.

We also follow BBDF in using successively more detailed industry classifications in explaining establishment-level wage variation. In the second row of the table, we use 2-digit NAICS codes, and show that this level of industry detail explains 36% of establishment-level wages. This is less than the 49% of establishment-level earnings variation that BBDF explain using 2-digit NAICS codes. However, while BBDF find that 4-digit NAICS codes can explain only 52% of establishment-level earnings variation, we find somewhat larger effects in that 4-digit NAICS codes can explain 57% of establishment-level wage variation, and 5-digit NAICS codes (not reported in BBDF) can explain 61% of establishment-level wage variation. Adding in state-level geographic variables and establishment size variables, we can explain 67% of establishment-level wage variation, while BBDF explain 58% of establishment-level earnings variation with similar variables. The conclusion from this analysis, and also from BBDF's similar analysis, is that a sizable amount of establishment-level wage variation remains unexplained by observable characteristics.

BBDF conclude their analysis with a call for more research into the link between the establishments where people work and the determinants of their pay. In the remainder of this paper, we demonstrate that one factor in this link is the distribution of employment by occupation within establishments—a measure not available in the data used by BBDF. We show that this measure is related to individual wages, and also that it plays a role in explaining differences in earnings between establishments.

Foster, Haltiwanger, and Troske (2004) find that 53 to 69 percent of wage variance in manufacturing is between establishments, and 90 percent of variance growth in manufacturing is between establishments. Barth, Bryson, Davis, and Freeman (in an earlier working paper version of their 2014 paper) find that on average 62 percent of variance in manufacturing is between establishments, and 27 percent (.034/.125 in Table 2) of variance growth in manufacturing is between establishments. We find in the OES data from 1999-2011 that on average 48% of manufacturing wage variance is between establishments, while 73% of the growth in manufacturing wage variance is between establishments.

[3] These groups were devised to use common industry groupings for OES data collected in the 1990s, using the SIC industry classification system, and OES data collected beginning in 2002, using the NAICS industry classification system. OES data for 2000 and 2001 were recoded so they can be analyzed with either system.

IV. Occupational Concentration: A link between establishments and occupations

IVa: Measuring Occupational Concentration

We use Herfindahl indices to measure the distribution of employment by occupation within establishments. In the rest of this paper, we shall refer to these Herfindahl indices as occupational concentration. Such indices are occupation-neutral, without any ranking of occupations by skill or wage levels. We use the structure of the Standard Occupational Classification system (SOC) to compute two establishment-level indices:

(2a) $\quad H_j^{801} = \sum_{k=1}^{801} \left(\frac{Employment\ in\ Occupation\ k\ in\ Establishment\ j}{Employment\ in\ Establishment\ j} \right)^2$

(2b) $\quad H_j^{22} = \sum_{k=1}^{22} \left(\frac{Employment\ in\ Occupation\ k\ in\ Establishment\ j}{Employment\ in\ Establishment\ j} \right)^2$

The first establishment-level index uses all 801 detailed civilian occupations at the 6-digit level of the Standard Occupational Classification system. This index varies from 1/801, or 0.001, (equal representation of all occupations) to 1 (perfect concentration). The second establishment-level index uses the 22 major occupational categories at the 2-digit level of the Standard Occupational Classification system included in the OES. This index varies from 1/22, or 0.045, (equal representation of all categories) to 1 (perfect concentration).

The categories of occupations that are separated in definition 2a but collapsed in definition 2b include occupations that perform related tasks, but can be paid very different wage levels. For example, dentists (occupation 29-1020) and dental hygienists (occupation 29-2021) are in the same broad 2-digit occupational category (29), but are paid very different wages. We use two different Herfindahls to measure whether the relationship between wages and our measures of occupational concentration are sensitive to the level of occupational aggregation in our data.

The average establishment (employment-weighted) has H^{22}=.545 and H^{801}=.354. In the underlying data, the average establishment (employment-weighted) has 5.60 2-digit occupational categories and 19.25 6-digit detailed occupations. Quite naturally these descriptive statistics vary by size class. Large establishments (those with more than 500 employees) have, on average, 11.85 2-digit occupational categories and 65.61 6-digit detailed occupations.

We next examine these two occupational concentration measures for specific occupations studied by Abraham and Taylor (1996) and Dey, Houseman, and Polivka (2010) in their work on outside contracting by employers. We restrict our data to establishments that employ janitors, and compare trends in our occupational concentration measures for these establishments to trends in janitorial services industry employment (this latter measure is calculated from the same OES data for NAICS 561720). The correlation between Herfindahl indices and traction of janitors working in the janitorial services industry over time is about .8 for both our H^{22} and H^{801} indices, with p values <.0001. We do the same for accountants, estimating employment in NAICS 54121. The correlations here are lower, at .40 for H^{22} and .46 for H^{801}, with p values of

.064 and .033 respectively. These examples show that our Herfindahl measures of occupational concentration are related to patterns of employment in industries linked to particular occupations.

The key question for our analysis is whether these establishment-level measures of occupational concentration can help explain the growth in wage inequality. For this to occur, occupational concentration measures must be related to wages, and either this relationship is strengthening over time, or measures of occupational concentration are increasing over time. We examine each of these in turn.

IVb: Relationships between Occupational Concentration Measures and Wages

We use regressions to show that both Occupational Concentration measures are strongly and significantly related to individual wages, across all occupations. We document this for individual worker i, employed by establishment j, with and without controlling for employees' occupations and establishments' industries, geographic states, and sizes, using the regression:

(3) $Ln(wage_{ijt}) = \alpha OccupationalConcentrationGroup_{jt} + \delta X_{ijt} + \varepsilon_{ijt}$,

where OccupationalConcentrationGroup is a vector of indicator variables calculated by rounding values of the establishment-level Herfindahls to the nearest hundredth. Control variables X include the survey date, occupation fixed effects, industry fixed effects, state fixed effects, and establishment size (we use fixed effects for establishment size classes as well as a continuous measure of establishment size).

The relationships between wages and our measures of occupational concentration are shown graphically in Figure 3. The left panels of Figure 3 give the raw data from regressions without controls for establishment or individual characteristics X, and the right panels show the wages for each group after controlling for observable characteristics. The top graphs labeled "detailed Herfindahl" show H^{801}, and the bottom graphs labeled "group Herfindahl" show H^{22}. The raw data clearly show that higher Herfindahl indices of occupational concentration are associated with lower wages. This negative relationship remains, albeit much smaller in magnitude, when we include controls for observable employee and employer characteristics.[4]

This negative relationship between wages and occupational concentration is quantified in Table 3, where the underlying regressions are of the form

(4) $Ln(wage_{ijt}) = \alpha OccupationalConcentration_{jt} +$
            $\beta OccupationalConcentration_{jt} * Date_t + \delta X_{ijt} + \varepsilon_{ijt}$,

where OccupationConcentration is now a continuous variable (rather than a vector of group indicators) and $Date_t$ is a measure of continuous time. When we restrict $\beta=0$ so that we estimate the relationships in Figure 3, estimates of the coefficients α from these regressions—with and

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[4] It is possible that the particularly low and high values of occupational concentration in Figure 3 are due to the absence of occupational heterogeneity in small establishments. However, the changes in slope at the extremes of the horizontal axis in Figure 3 remain when we drop establishments with less than 25 employees from our estimating regressions.

without additional controls—show that increased occupational concentration is significantly associated with lower wages. Estimates of the coefficient β (shown here in decade units of time) in column 2 of Table 3 show that the negative relationship between individual wages and the establishment's occupational concentration has significantly strengthened over time, although this time effect declines dramatically when control variables are added (column 4 of Table 3).

We repeat these regressions within each detailed occupation in the OES separately (omitting occupation from the set of X variables). We find that this negative relationship between the occupational concentration of employing establishments and wages for individual workers exists within a wide variety of occupations, using either measure of occupational concentration, with and without other establishment controls. Without controls, occupations with negative and statistically significant relationships (at the $p < 0.05$ level) between wages and occupational concentration account for 61.5% of all employment, and including those with negative but not statistically significant relationships increases this figure to cover 71.0% of all employment. (Similar figures for the detailed measure of occupational concentration are 63.4% and 73.0% of all employment). The addition of industry, state, and establishment size controls makes little difference to these percentages. These relationships are similar in magnitude for occupations in different parts of the wage distribution. Overall, occupation-specific versions of the α coefficients from equation (4) have close to 0 correlation with the log wages of each occupation.

Since Occupational Concentration is defined at the establishment-level, we return to the framework of equation (1) and ask how much of the wage variance between establishments can be explained by the occupational concentration measures. In the November 2007 data, a regression of average establishment wages on the broad occupational Herfindahl index has an R-squared value of .15, and a regression on the detailed occupation Herfindahl index also has an R-squared value of .15. This is similar to the amount of establishment-level wage variation that is explained by Industry Groups. When we add Occupational Concentration to other variables explaining establishment-level wages in column 2 of Table 2, we find that the additional explanatory power of Occupational Concentration falls as the level of detail in industry classification rises. When industry is classified in only 13 broad groups, adding Occupational Concentration variables increases the amount of wage variance explained from 32% to 43% (see column 4 of Table 2). However, when industry is classified at the very detailed 5-digit NAICS level, adding Occupational Concentration variables only increases the amount of wage variance explained from 67% to 68%. Nonetheless, even with such detailed measures of industry, Occupational Concentration continues to increase the amount of establishment-level wage variance explained.

IVc: Trends in Occupational Concentration measures

We now turn to time trends in occupational concentration measures. Finding that occupational concentration has increased during the 1999 to 2012 time period would be a general indication of increased sorting of particular kids of work between establishments. Furthermore, observing changes in both broad and detailed occupational concentration would be an indication of a changing type of work done by an establishment. For example, a manufacturing plant that outsources its janitors would show increasing occupational concentration for both indices. In

contrast, observing changes in detailed occupational concentration without similar changes in broad occupational concentration would be an indication that an establishment is changing the specific occupations they employ (perhaps changing production processes or purchasing inputs from certain very specific tasks), but not changing the overall type of work done at that establishment.

Figure 4 shows the time trend in mean values for both measures of occupational concentration, from 1999 to 2012. In the left panels which reflect the raw data, we see some evidence of increases in mean values of both measures, although these measures are generally higher in the November OES panels than the May panels. However, looking closely at the magnitude of the vertical axis, we conclude that any increases in occupational concentration are economically small. For example, the broad measure increases from roughly .535 to .550, and the detailed measure increases from roughly .35 to .36.

In the right panels of the figure, we examine trends in mean values of occupational concentration after controlling for establishment characteristics, plotting coefficients α from regressions

(5) $OccupationalConcentration_{jt} = \alpha Date_t + \delta X_{jt} + \varepsilon_{jt},$

These regression results are given in Table 4. The simple specification in column 1 shows the increasing time trend, with a statistically significant coefficient. In results not shown, we add controls only for detailed occupation. These results are similar to those shown in column 1. This suggests that these increases in occupational concentration are not due only to changes in the overall occupational distribution, such as the changes due to employment polarization (as described by Autor, Katz, and Kearney, 2006, and by Autor and Dorn, 2013). However, after controlling for changes in other factors (particularly controlling for industry), results in column 2 show no increase in mean values of Occupation Concentration measures.

Table 4 also gives regression results for time trends in employment in particularly concentrated establishments; those with occupational concentration measures of .8 or higher. Here again, a simple specification in column 3 shows an increasing time trend in employment in highly occupational concentrated establishments. After controlling for changes in other factors, column 4 continues to show a small but statistically significant increase in employment at highly-concentrated establishments using the detailed-occupation Herfindahl, but not when using the broad-occupation Herfindahl measure of occupational concentration.[5]

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[5] Our empirical analysis to this point work has focused on measures of occupational concentration at the establishment level, because establishments are the sampling unit of the OES. However, the OES does contain the Employer Identification Number (EIN) which identifies firms for Federal tax reporting purposes. Using these EINs to identify firms, we find that the relationship between EIN-level occupational concentration and wages is very similar to the results described above. Results for time trends with EIN-level occupational concentration measures are somewhat weaker than described above, which suggests that multi-establishment employers are segregating different occupations into different establishments.

V. Changes in Wage Inequality over Time

The strong relationship between establishment-level occupational concentration and wages, together with some evidence for growth in this relationship as well as growth in occupational concentration (although both of these latter disappear once we control for observables), suggests that changes in occupational concentration over time may explain some of the growth in wage inequality. In this section, we conduct a reweighting exercise in order to understand how much of increasing wage inequality in the OES from Fall 1999 to November 2011 can be attributed to changes in the employment composition of observable characteristics such as industry, establishment size, geography, and occupation, as well as our measures of occupational concentration. We use the method of DiNardo, Fortin, and Lemieux (1996), hereafter DFL,[6] to calculate counterfactual wage distributions based on the OES wage intervals, as well as counterfactual variance estimates.

An example may illustrate what we hope to learn from this reweighting exercise. We know that there has been employment polarization during the last 10-20 years: see Autor, Katz, and Kearney (2006), Goos and Manning (2007), Goos, Manning, and Salomons (2009), and Abraham and Spletzer (2010). Using the OES data, and defining "jobs" by industry and occupation, Abraham and Spletzer show that the share of both low-wage and high-wage jobs has risen from 1996 to 2004, whereas the share of middle-wage jobs has fallen (employment growth has polarized). These changes in the distribution of occupations should lead to increased wage inequality. The reweighting exercise allows us to hold constant the employment composition of occupations and industries at their 1999 values when calculating the variance of log real hourly wages in 2011, and the resulting counterfactual wage variance quantifies the magnitude of polarized employment growth on the increasing wage variance.

We run DFL-type reweightings for the observable characteristics of broad industry groups (for comparability between the 1999 data, collected using SIC, and the 2011 data, collected using NAICS), state, establishment size, occupation (at the 3-digit SOC code level), and our two measures of occupational concentration. These measures of occupational concentration are entered into the reweighting as categorical variables by dividing them into groups at the first decimal place. We run these reweightings for all possible sub-sets of these 6 variables—a total of 63 possible combinations. Noting that BBDF find that much more of between-establishment earnings growth over time can be explained with more detailed industry measures, we repeat this exercise, using detailed industry at the 4 digit NAICS instead of the broad industry groups. However, in order to use the more detailed industry measure we must begin the reweighting exercise with data from Fall 2000, when NAICS coding is first available in the OES data, instead of Fall 1999. For clarity, we present here only the results of the reweighting exercise using the more detailed industry data, but the conclusions of the two exercises are very similar.

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[6] The DiNardo, Fortin, and Lemieux (1996) methodology of creating counterfactual distributions for a later year if observable characteristics were held fixed at their distribution in an earlier year is to (1) combine the data for the earlier and later years and run a probit regression of the probability that an observation with a particular set of observable characteristics came from the earlier year and then (2) use the predicted values from this probit regression to create new weights for each observation in the later year.

The top panel of Table 5 documents some basic descriptive statistics of the wage distribution. The variance of ln wages in 2000 is .3520, and increases to .4018 in 2011. The between establishment variance rises from .1884 in 2000 to .2288 in 2011.

Results of reweightings for each observable characteristic alone are shown in rows 1-6 of the bottom panel of Table 5, with reweightings for selected combinations of these characteristics shown in rows 7-12. As shown in Table 5, occupation (at the 3-digit SOC level) and industry (at the 4 digit NAICS code level) are the variables which alone explain the largest amount of overall wage variance growth from Fall 2000 to November 2011. Reweighting observations in November 2011 to the Fall 2000 distribution of 3-digit occupations (row 4) would reduce overall ln wage variance in 2011 from the measured variance of .4018 to .3853, a decrease representing 33% of ln wage variance growth from Fall 2000 to November 2011. Row 4 also shows a decrease of 41% of ln wage variance growth between establishments. Changes in the distributions of employment by detailed industry (row 1) and geographic states (row 2) can also explain some of overall ln wage variance growth as well as ln wage variance growth between establishments. Changes in the distributions of employment by occupational concentration alone (rows 5 and 6) explain almost none of overall ln wage variance growth, although they do explain some of the growth of wage variance between establishments.

Reweighting by multiple characteristics simultaneously does not always increase the overall amount of ln wage variance growth explained—using all of our possible reweighting variables (row 7 of Table 5), results in less overall variance explained than using only State, Occupation, and Occupational Concentration (rows 8 and 9). Combining groups of characteristics to reweight to their Fall 2000 distributions, we find that the greatest amount of overall ln wage variance explained (38%) is the combination shown in row 8. This is a combination of State, Occupation, and both Herfindahl indices of Occupational Concentration. Surprisingly, this combination does not include detailed industry—all of the explanatory power of detailed industry to explain overall ln wage variance growth has been absorbed by the combination of State and Occupation. This combination of reweighting characteristics can also explain 50% of the growth in the between-establishments component of ln wage variance growth from Fall 2000 to November 2011. We find nearly identical results when we use only the Broad Occupational Category Herfindahl index (row 9) or, in results not shown, when we use only the Detailed Herfindahl index. Removing both measures of Occupational Concentration from this reweighting, as shown in row 10, has little impact on the amount of overall ln wage variance growth explained, but it reduces the amount of the growth in the between-establishments component of ln wages that can be explained (from 50% to 43%).

The combination of characteristics that best explains the between-establishments component of ln wage variance growth between Fall 2000 and November 2011 is shown in row 11 of Table 5. This combination includes detailed industry as well as State, Occupation, and both measures of Occupational Concentration. Combined, reweighting these variables to their Fall 2000 distributions can explain 52% of the between-establishments component of the growth in ln wage variance during this time period. Without either measure of Occupational Concentration, no combination of reweighting characteristics can explain more than 46% of the between-establishments component of the growth in ln wage variance during this time period (shown in row 12).

Overall, the reweighting exercise presented in Table 5 shows that Occupational Concentration—by either of our measures—has at most a small role in explaining the overall growth in variance between 2000 and 2011. However, Occupational Concentration variables can explain a portion of the growth in the between-establishments component of the ln wage variance growth during this period that cannot be explained by other available individual or establishment-level variables.

We have examined the sensitivity of the results in Table 5 to the choice of specific start and end dates (reweighting 2011 data to the distribution of explanatory variables in 2000). Focusing on similar stages of the business cycle, we have reweighted 2007 data to 2000 distributions, and we have reweighted 2011 data to 2003 distributions. These exercises do not change our substantive conclusion that occupational concentration variables have a small amount of explanatory power for explaining the rise in total variance and somewhat more power to explain the rise in between establishment variance.

VI. Discussion and Conclusion

In this paper, we examine the concentration of occupations by establishment and what this concentration means for individual wages and for the distribution of wages within and between establishments. Occupational concentration is a particular form of worker sorting to establishments, which has not been well-examined in the U.S. before. We document increases in occupational concentration that do not appear to be driven by the changing distribution of occupations (employment polarization), but do appear to be largely explained by other establishment characteristics, such as industry. One potential explanation for these changes is that they may result from establishments increasingly specializing in particular tasks, and contracting out other tasks, as described by Abraham and Taylor (1996) and Goldschmidt and Schmieder (2015). We find that more concentrated establishments pay lower wages, even after controlling for employee occupation, geography, establishment size, and very detailed measures of establishment industry. The relationship between increased concentration of occupations and lower wages holds within a variety of occupations, including both low-wage and high-wage occupations.

Many authors have noted the large and growing role of employers in wage inequality. We find in our data that more than half of wage dispersion and 92% of the recent growth in wage dispersion is between establishments rather than within establishments. We find that occupational concentration can explain as much as 15% of establishment-level wage variation in the year 2007. Combining occupational concentration with other establishment-level measures, such as detailed industry and establishment size, we can explain as much as 68% of all establishment-level wage variation. Combining occupational concentration with individual and establishment level characteristics, we can explain as much as 52% of the growth in wage inequality between establishments over the 2000 – 2011 period. However, the contribution of occupational concentration by itself to the growth in between-establishment wage inequality is small.

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Figure 1: OES Survey Form (abridged)

OCCUPATIONAL TITLE AND DESCRIPTION OF DUTIES		NUMBER OF EMPLOYEES IN SELECTED WAGE RANGES (Report Part-time Workers According to an Hourly Rate)												
		A	B	C	D	E	F	G	H	I	J	K	L	T
	Hourly (part-time or full-time)	under $7.50	$7.50– 9.49	$9.50– 11.99	$12.00– 15.24	$15.25– 19.24	$19.25– 24.49	$24.50– 30.99	$31.00– 39.24	$39.25– 49.74	$49.75– 63.24	$63.25– 79.99	$80.00 and over	Total Employment
	Annual (full-time only)	under $15,600	$15,600– 19,759	$19,760– 24,959	$24,960– 31,719	$31,720– 40,039	$40,040– 50,959	$50,960– 64,479	$64,480– 81,639	$81,640– 103,479	$103,480– 131,559	$131,560– 166,399	$166,400 and over	
Architects, Except Landscape and Naval - Plan and design structures, such as private residences, office buildings, theaters, factories, and other structural property. 17-1011		A	B	C	D	E	F	G	H	I	J	K	L	T
Landscape Architects - Plan and design land areas for such projects as parks and other recreational facilities, airports, highways, hospitals, schools, land subdivisions, and commercial, industrial, and residential sites. 17-1012		A	B	C	D	E	F	G	H	I	J	K	L	T
Cartographers and Photogrammetrists - Collect, analyze, and interpret geographic information provided by geodetic surveys, aerial photographs, and satellite data. Research, study, and prepare maps and other spatial data in digital or graphic form. May work with Geographic Information Systems (GIS). 17-1021		A	B	C	D	E	F	G	H	I	J	K	L	T
Surveyors - Make exact measurements and determine property boundaries Provide data relevant to the shape, contour, gravitation, location, elevation, or dimension of land or land features on or near the earth's surface. 17-1022		A	B	C	D	E	F	G	H	I	J	K	L	T
Aerospace Engineers - Perform a variety of engineering work in designing, constructing, and testing aircraft, missiles, and spacecraft. 17-2011		A	B	C	D	E	F	G	H	I	J	K	L	T
Agricultural Engineers - Apply knowledge of engineering technology and biological science to agricultural problems concerned with power and machinery, electrification, structures, soil and water conservation, and processing of agricultural products. 17-2021		A	B	C	D	E	F	G	H	I	J	K	L	T
Biomedical Engineers - Apply knowledge of engineering, biology, and biomechanical principles to the design, development, and evaluation of biological and health systems and products, such as artificial organs and medical information systems. 17-2031		A	B	C	D	E	F	G	H	I	J	K	L	T
Chemical Engineers - Design chemical plant equipment and devise processes for manufacturing chemicals and products by applying principles and technology of chemistry, physics, and engineering. 17-2041		A	B	C	D	E	F	G	H	I	J	K	L	T

Figure 2: Variance Between and Within Establishments in the OES
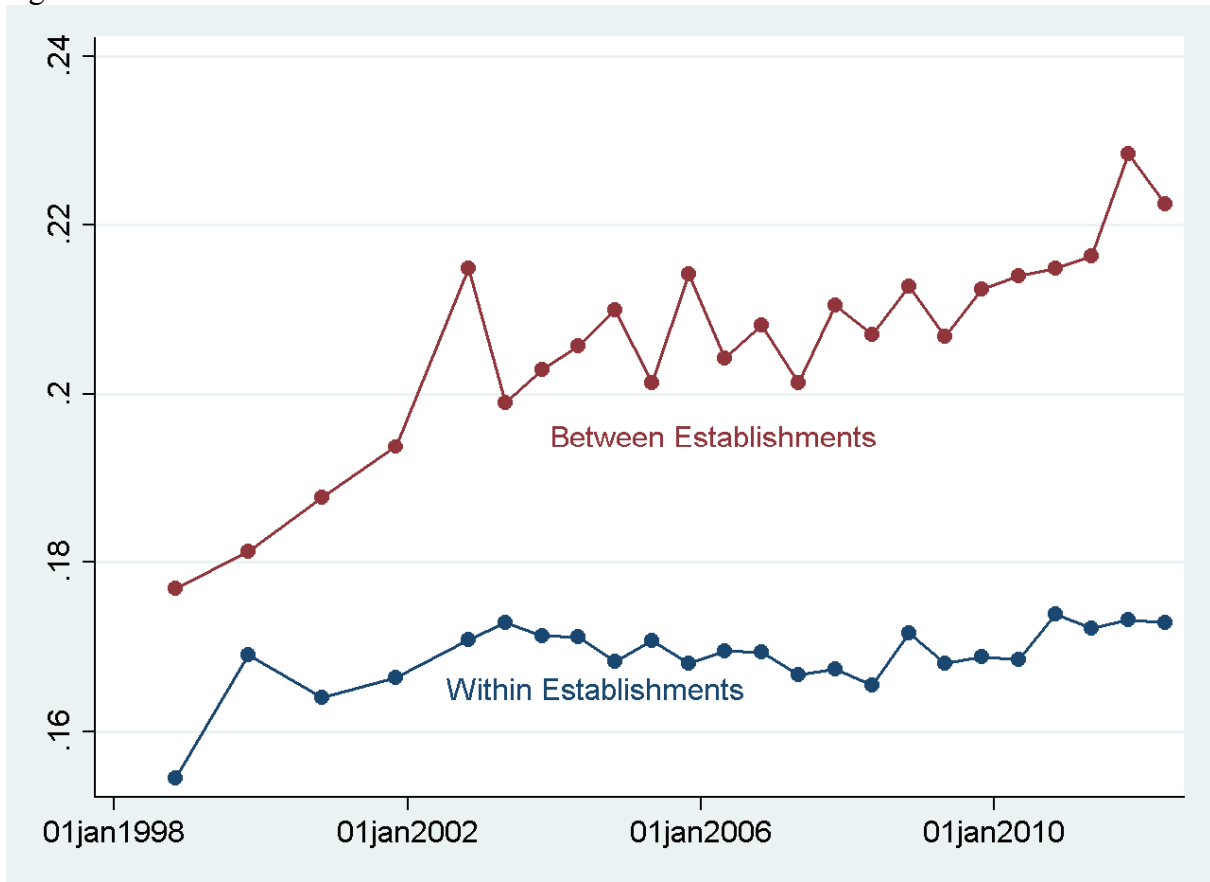
Notes: Figure computed from the combined 1998-May 2012 panels of the Occupational Employment Survey, private-sector only.

Figure 3: Relationships between Wages and Occupational Concentration
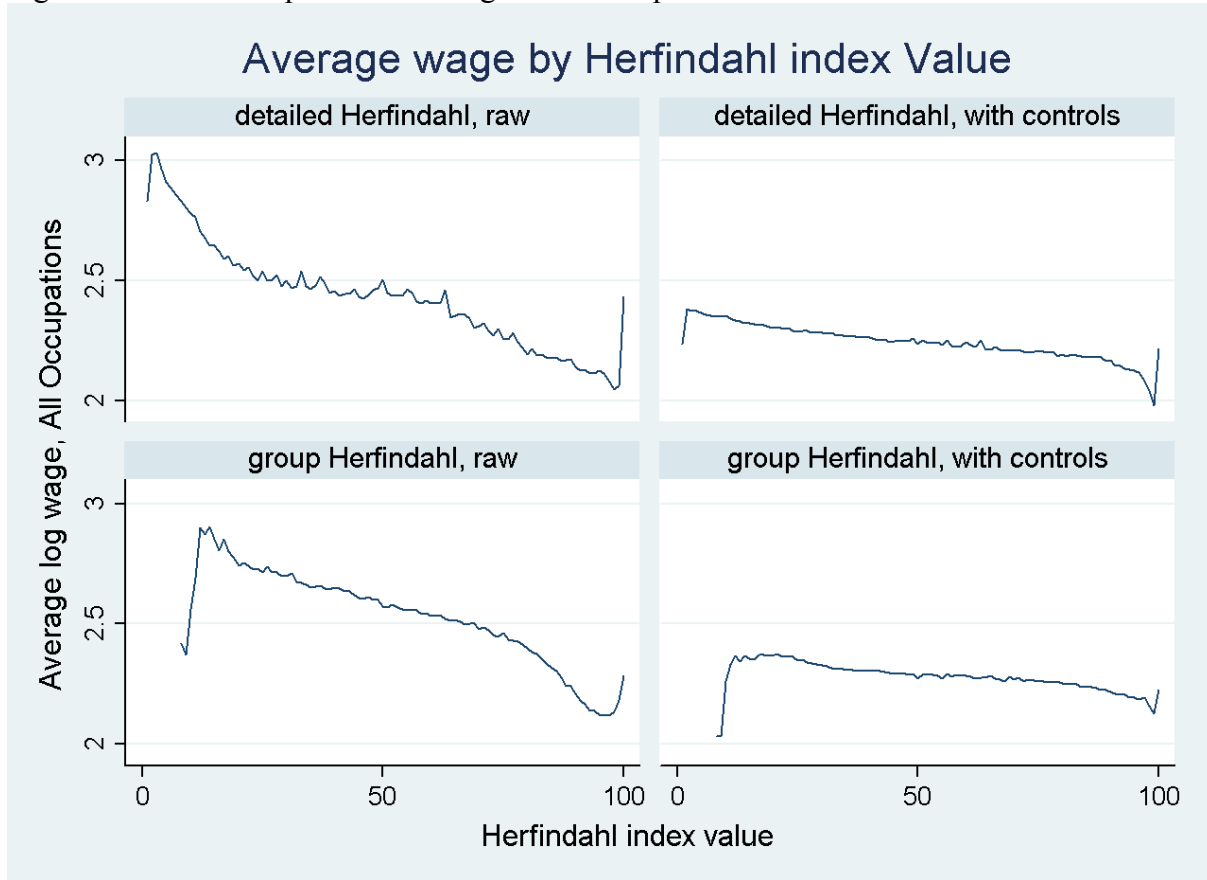
Notes: the average wages plotted here are the set of α coefficients from regressions of the form Ln(wage$_{ijt}$) = αOccupationalConcentrationGroup$_{jt}$ + δX$_{ijt}$ + ε$_{ijt}$, where Occupation Concentration Groups are formed by rounding each Occupation Concentration variable to the nearest hundredth, and X includes survey date fixed effects, occupation fixed effects, broad industry groups, state fixed effects, and establishment size (we use fixed effects for establishment size classes as well as a continuous measure of establishment size). All unimputed OES private-sector data from Fall 1999 to May 2012 are used in the regressions. Each regression is based on about 43,511,000 occupation – wage interval observations.

Figure 4: Trends in Means of Occupational Concentration
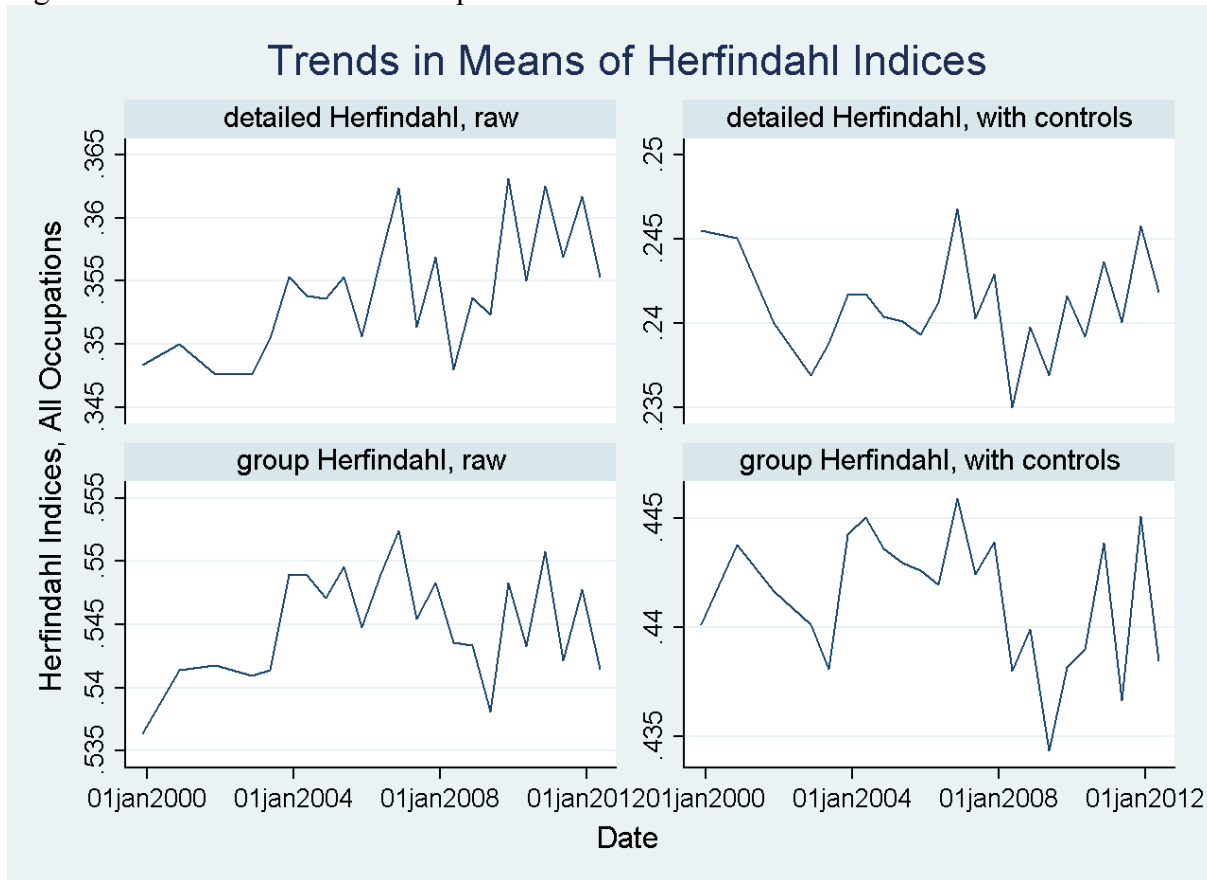
Note: These are plots of coefficients α from regressions OccupationalConcentration$_{jt}$ = αDate$_t$ + δX$_{jt}$ + ε$_{jt}$, where X includes survey date fixed effects, broad industry groups, state fixed effects, and establishment size (we use fixed effects for establishment size classes as well as a continuous measure of establishment size). All unimputed OES private-sector data from Fall 1999 to May 2012 is used in the regressions. Each regression is based on about 3,576,000 establishment-date observations.

Table 1: Variance of Log Real Hourly Wage and its growth by Industry Group, OES Fall 1999- November 2011 Averages and Growth

Industry Group	Average Logged Wage Variance	Percent Within Establishments	Percent Between Establishments	Overall Logged Wage Variance Growth	Percent Within Establishments	Percent Between Establishments
Mining	0.2878	54.9%	45.1%	0.0670	28.2%	71.8%
Retail Trade	0.2340	64.0%	36.0%	-0.0158	43.7%	55.7%
Wholesale, Trans, Util	0.3175	56.6%	43.4%	0.0127	66.1%	33.1%
Construction	0.2480	55.2%	44.8%	0.0069	29.0%	71.0%
Manufacturing	0.3081	52.5%	47.5%	0.0579	26.9%	73.1%
Information	0.3741	50.9%	49.1%	0.0534	12.5%	87.5%
Finance & Real Estate	0.3975	55.2%	44.8%	0.0270	-34.8%	135.2%
Prof & Bus Services	0.4526	39.8%	60.2%	0.0465	12.7%	87.3%
Educ Services	0.3418	69.2%	30.8%	0.0707	55.4%	44.6%
Health & Social Assist	0.3659	59.8%	40.2%	0.0497	0.6%	99.6%
Arts & Entertainment	0.2979	60.9%	39.1%	0.0614	15.3%	84.5%
Food & Lodging	0.1306	68.7%	31.3%	-0.0102	84.3%	15.7%
Other Services	0.2823	44.6%	55.4%	0.0408	0.7%	99.3%
All Industries	0.3764	45.0%	55.0%	0.0514	8.2%	91.8%

Table 2: R-squared values from establishment-level regressions of November 2007 OES Data

		Establishment-level Regressors			
Level of Industry Detail	Industry Alone	Industry + Geography + Establishment Size	Industry + Geography + Estab Size + Occupational Group Herfindahl	Industry + Geography + Estab Size + Detailed Occupation Herfindahl	"Establishment effect"
Industry Groups	0.18	0.32	0.42	0.43	0.57
2 digit NAICS	0.36	0.47	0.52	0.52	0.48
3 digit NAICS	0.48	0.56	0.59	0.59	0.41
4 digit NAICS	0.57	0.63	0.66	0.65	0.35
5 digit NAICS	0.61	0.67	0.68	0.68	0.32

Notes: These are R-squared values from establishment level regressions for November 2007 OES data, of the form $Ln(wage_j) = \alpha Industry_j + \beta State_j + \chi EstabSize_j + \varepsilon_j$. "Establishment effects" are calculated as residuals, based on the greatest R-squared value on each line.

Table 3: Regressions of log wages on measures of Occupational Concentration

Panel A: Herfindahl of occupational concentration at the broad occupational level (H^{22})

	(1)	(2)	(3)	(4)
Occupational Concentration	-0.655	-0.399	-0.167	-0.222
[t-stat]	[-1940.1]	[87.29]	[-625.01]	[80.54]
Occupational Concentration * Date		-0.055		0.012
[t-stat]		[56.41]		[20.12]
R-Squared	0.08	0.08	0.67	0.67
Controls for:				
Survey Date Fixed Effects	Yes	Yes	Yes	Yes
6-Digit Occupation Effects			Yes	Yes
Industry, Size, State			Yes	Yes

Panel B: Herfindahl of occupational concentration at the detailed occupational level (H^{801})

	(1)	(2)	(3)	(4)
Occupational Concentration	-0.548	-0.236	-0.181	-0.175
[t-stat]	[-1605.9]	[-51.22]	[-661.78]	[-63.78]
Occupational Concentration * Date		-0.067		-0.001
[t-stat]		[-67.89]		[-2.20]
R-Squared	0.06	0.06	0.67	0.67
Controls for:				
Survey Date Fixed Effects	Yes	Yes	Yes	Yes
6-Digit Occupation Effects			Yes	Yes
Industry, Size, State			Yes	Yes

Notes: These are regressions of the form $Ln(wage_{ijt}) = \alpha OccupationalConcentration_{jt} + \beta OccupationalConcentration_{jt} * Date_t + \delta X_{ijt} + \varepsilon_{ijt}$, where X includes survey date fixed effects, occupation fixed effects, broad industry groups, state fixed effects, and establishment size (we use fixed effects for establishment size classes as well as a continuous measure of establishment size). All unimputed OES private-sector data from Fall 1999 to May 2012 are used in the regressions. Each regression is based on about 43,511,000 occupation – wage interval observations.

Table 4: Changes in Occupational Concentration over time

Panel A: Herfindahl of occupational concentration at the broad occupational level (H^{22})

	Overall		Indicator for values above .8	
	(1)	(2)	(3)	(4)
Date (in decade units of time)	0.003	-0.002	0.011	-0.002
[t-stat]	[23.81]	[-28.16]	[61.04]	[-15.85]
R-Squared	0.00	0.42	0.00	0.34
Controls for:				
6-Digit Occupation Effects		Yes		Yes
Industry, Size, State		Yes		Yes

Panel B: Herfindahl of occupational concentration at the detailed occupational level (H^{801})

	Overall		Indicator for values above .8	
	(1)	(2)	(3)	(4)
Date (in decade units of time)	0.008	-0.0001	0.037	0.002
[t-stat]	[73.08]	[-7.77]	[62.06]	[17.22]
R-Squared	0.00	0.45	0.00	0.26
Controls for:				
6-Digit Occupation Effects		Yes		Yes
Industry, Size, State		Yes		Yes

Note: These are coefficients α from regressions of the form $OccupationalConcentration_{jt} = \alpha Date_t + \delta X_{jt} + \varepsilon_{jt}$, where X includes broad industry groups, state fixed effects, and establishment size (we use fixed effects for establishment size classes as well as a continuous measure of establishment size). All unimputed OES private-sector data from Fall 1999 to May 2012 is used in the regressions. Each regression is based on about 43,511,000 occupation-wage cells from 3,576,000 establishment-date observations.

Table 5: Results for DFL-style reweightings of November 2011 establishment and employee characteristics to their Fall 2000 distributions:

2000 ln wage var:	0.3520		2000 Btw estab var:	0.1884			2000 Wtn estab var:		0.1637
2011 ln wage var:	0.4018		2011 Btw estab var:	0.2288			2011 Wtn estab var:		0.1729
Increase:	0.0497		Increase:	0.0405			Increase:		0.0093

Variances after reweighting 2011 data to 2000 chars:

	NAICS4	State	Size	Occup	Herf-22	Herf-801	Overall Var	Overall Explained	Between Estabs Var	Between Estabs Explained	Within Estabs Var	Within Estabs Explained
1:	Y						0.3915	21%	0.2192	24%	0.1723	7%
2:		Y					0.3985	7%	0.2267	5%	0.1718	12%
3:			Y				0.4050	-7%	0.2299	-3%	0.1751	-24%
4:				Y			0.3853	33%	0.2123	41%	0.1731	-2%
5:					Y		0.4012	1%	0.2256	8%	0.1756	-28%
6:						Y	0.4025	-1%	0.2267	5%	0.1758	-31%
7:	Y	Y	Y	Y	Y	Y	0.3879	28%	0.2107	45%	0.1772	-46%
8:		Y		Y	Y	Y	0.3831	38%	0.2086	50%	0.1744	-16%
9:		Y		Y	Y		0.3831	38%	0.2090	49%	0.1741	-13%
10:		Y		Y			0.3835	37%	0.2113	43%	0.1723	7%
11:	Y	Y		Y	Y	Y	0.3840	36%	0.2077	52%	0.1763	-36%
12:	Y	Y		Y			0.3841	36%	0.2102	46%	0.1739	-10%

Note: see section Vb for a detailed explanation of this table