Labor-Market Concentration and Labor Compensation*

Yue Qiu†
Aaron Sojourner‡

October 18, 2019

Abstract

This paper estimates the effect of labor-market concentration on labor compensation across the U.S. private sector since 2000. We distinguish between concentration in local labor markets versus local product markets, guarding against bias from confounded product-market concentration. Analysis extends beyond wages to rates of employment-based health insurance coverage. Estimates suggest negative effects of labor-market concentration on labor compensation. This comes through both reducing the human-capital level of those in the market and reducing pay conditional on human-capital level. Higher product-market concentration exacerbates and higher unionization rates mitigates these effects.

Keywords: labor-market concentration, wages, health insurance, unions.
JEL: J31, J32, J42, L13, J51

†Fox School of Business, Temple University. yue.qiu@temple.edu
‡Carlson School of Management, University of Minnesota. asojourn@umn.edu

1 Introduction

We study effects of local labor-market concentration on wages in the U.S. economy. Workers may be subject to employer market power due to a lack of competition between employers, a literal form of monopsonistic competition in particular that is one among many varieties of employer wage-setting power derived from upward-sloping labor supply curves facing firms (Manning, 2011; Naidu et al., 2018). Employers in more-concentrated labor markets, proxied here by a higher Herfindahl-Hirschman Index (HHI) on employment shares in a market, may have the wage-setting power to markdown workers' wages below their marginal product, analogously to the how sellers in monopolistically-concentrated product markets may have power to markup consumer prices above their marginal cost. Given that U.S. workers' wages, below the top end, have stagnated for decades (Shambaugh et al., 2017), investigating potential avenues for increasing them is of first-order economic importance (Shambaugh and Nunn, 2018). We define labor markets as the combination of an occupation and a commuting zone and focus on the relationship between changes in concentration and changes in wages within labor markets using market fixed effects and market-specific time trends. We use pooled cross-sections of worker-level wage data from the 2000 Decennial Census and the American Community Survey in each year from 2005 to 2014. Distinct from the prior literature, our contributions include controlling for important potential confounding factors, such as the product-market concentration of the worker's local industry and the worker's individual human capital characteristics. This is possible because, unlike the prior literature, we analyze worker-level data with each individual's wage, industry, occupation, and human-capital characteristics. We also expand the analysis of effects beyond wages to include employment-based health insurance as well.

Recent work finds evidence of such concentration based on firms' shares of vacancy postings in an occupation-locale during 2010 to 2013 Azar et al. (2017) and in 2016 Azar et al. (2018). The former presented evidence that greater concentration caused lower wage, measuring wage as posted wage among vacancies including a posted wage. The latter focuses on how to define local labor markets and offers cross-sectional description of concentration across markets but does not analyze relation to wages. Hershbein et al. (2019) uses data similar to this but focuses on how concentration affects demand for skill as expressed in the text of vacancy postings and finds greater concentration associated with both lower wages and stronger demand for greater skill, even within occupation, an effect they term "upskilling." Because these three papers rely on online archives of vacancy postings, their measures of concentration derive from vacancy shares, rather than employment shares.[1]

Four recent papers leverage the Census Longitudinal Business Database (LBD) to measure labor-market concentration at the industry-locale-year level using employment shares, rather than vacancy shares. Benmelech et al. (2019) focus on a handful of industries within manufacturing and define a labor market at the industry-county (commuting zone) level. They focus here because they can get establishment-level measures of labor productivity, which provides an important control variable in explaining establishment-year average wage. They find evidence that greater concentration causes slightly lower wages. Also, this effect is weaker in industries with higher, national-level unionization rates. Rinz (2018) expands this approach to the whole economy from 1976 to 2015, again focusing on concentration within an industry-locale and using commuting zone as the measure of locale. He produces the first evidence of trends in local labor market concentration broadly and finds evidence of effects on individual wages. He finds a positive effect, contrary to expectations, in difference-in-difference models without instruments. The sign reverses to a negative effect, consistent with increasing concentration lowering wages, when using an instrumental variable based on contemporaneous changes in the structure of the same kind of labor market across other locales. Lipsius (2018) also analyzes the LBD defining labor markets along local industry lines but uses LBD's establishment average wage aggregated up to the local firm level, rather than linking to individual worker-level wages. He interprets the evidence in the context of more well-developed theoretical model, which highlights the importance of controlling for labor

[1]Hershbein et al's analysis of effects on wages includes occupation and locale effects but not occupation-locale (market) effects.

market size and labor productivity. Berger et al. (2019) uses a similar empirical strategy and add value by interpreting estimates in the context of a general-equilibrium model and to assess welfare implications of changes in labor-market concentration and of minimum-wage policy changes.

We make four main contributions relative to the prior literature. First, we distinguish local labor-market concentration in an occupation-year from local product-market concentration in an industry-year to build more-credible estimates. Industries describe how firms face consumers. Occupations describe how they face workers. We measure both and control for the latter when trying to measure the effect of the former. This is conceptually critical because the two are easily confounded. For example, if there are only two nursing homes in town and they are the only local employers of registered nurses, they will have power in both the product and labor markets. Industry concentration may generate economic rents for firms from consumers, which might provide a basis for rent-sharing with employees and higher wages. Occupational concentration may generate economic rents for firms from workers by suppressing wages. Because product market and labor market concentration may move together, the absence of product-market concentration from the prior literature's analysis creates a risk of omitted-variable bias. In this regard, the most-similar paper is Prager and Schmitt (2019). They focus on the U.S. hospital industry specifically and use changes in average wages within a few occupational groups among hospitals in a locale following hospital mergers, leveraging hospital-year-occupational group data on employment and wage along with data on mergers. They find negative effects on wage growth.

We build our measures of local concentration from the Dun & Bradstreet (D&B) database of U.S. establishments. For each establishment-year, we observe measures of establishment name, parent firm, address, industry, employment, and revenue. The D&B data have a similar structure to the Census LBD used by Benmelech et al. (2019), Rinz (2018) and Lipsius (2018). Our measures of labor-market concentration derived from the D&B data show similar changes over time to those Rinz produced from the Census LBD, though definitions and levels differ somewhat. To harmonize with the Census worker-level micro-data, we define locale as the 1990 commuting zone (CZ). We define local product-market concentration based on revenue shares across firms within an industry-CZ. If there are multiple establishments with the same ultimate parent firm in the same industry-CZ, they are pooled together to count as one firm.

We want to focus on occupational shares to define labor-market concentration. We do not observe employment by occupation in the D&B. To overcome this, we harness estimates of the occupational distribution of employment within each industry-year from the Census microdata nationally. We impute employment by occupation to each establishment as the product of its employment level times its industry-year occupational distribution. From there, we compute a measure of employment shares across firms within each occupation-locale-year, which we use as the primary predictor of interest. This approach to measuring occupational employment is novel in this literature.

Though we use different data and labor-market definitions to measure labor-market concentration than Rinz, Hershbein et al, and Lipsius do, we also find that average concentration levels nationally now are below 2000 levels, though up since the Great Recession. Labor-market concentration may have been pushing down labor compensation throughout the period, but the level of concentration doesn't appear to have risen over this period.

Empirically, our results largely reinforce the negative wage effects estimated by the prior literature. Estimates from our OLS analysis yield a different result – a very small positive or null effect, echoing Rinz (2018). However, estimates from IV analysis following Azar et al. (2017)'s use of a function of each occupation's average number of employing firms in other locales as an instrument for each labor market's own labor-market concentration find evidence of a substantial negative effect of labor-market concentration on wages. Showing that the basic results of Benmelech et al. (2019), Azar et al. (2017), Rinz (2018), Hershbein et al. (2019), Lipsius (2018), and Berger et al. (2019) that labor-market concentration negatively affects wages holds up with occupationally-defined labor markets, employment-based (rather than vacancy-based) HHI, conditional on controls for product-market concentration and labor-market-specific unobservable trends and other more-aggressive sets of fixed effects is our main contribution. Relative to Prager and Schmitt (2019), we generalize across all industries and occupations and use different variation in concentration.

Second, in trying to understand how concentration affects wage, we look at changes in the human capital characteristics of a labor-market's workers as a potential mechanism. If average wage is observed to fall as a labor market's concentration rises, this is likely to happen by a combination of affecting pay of workers who remain in the industry and changing the composition of who works there. Our analysis suggests that changes in workforce composition following changes in concentration explain some but not all of the effects of concentration on wages. Prior literature have not offered evidence on the relative importance of these channels. In their study of job-vacancy postings' text and aggregate wages, Hershbein et al. (2019) find evidence that labor-market concentration leads firms to demand workers with higher skill levels within occupation. If correct, this mechanism would generate a positive correlation between concentration and wage through worker skill but, conditional on skill, a negative effect on wage may appear and the overall effect on wage is ambiguous. They do not measure the skill level of employed workers (only of desired skill in employers' vacancy postings) and do not test for it directly. We find evidence that increasing concentration leads to a lower share of college-educated workers in the market. As concentration increases, the share of workers with a college degree falls. Adding controls for individual workers' education, age, race, ethnicity, marital status, birthplace, and whether the job is fulltime absorbs a large share of the labor-market concentration effect. While employers may ask for more skill, their desire for lower wages seems to win out. The estimated effect of concentration on wages conditional on workers' human capital characteristics is substantially less negative than its unconditional effect. Prior research has not used worker characteristics this way.[2]

[2]Rinz (2018) explores the possibly heterogeneous effects of concentration in different worker subgroups – among whites, African-Americans, low-education, high-education, young, middle-aged, older, men, or women – but doesn't examine the effect of concentration on individual worker's wage while controlling for the full vector of worker characteristics.

Third, beyond looking at the effect on workers' wages as the prior literature has, we also look at the effect of labor-market concentration on workers' probability of employment-based health insurance coverage, a substantial component of labor compensation. In recent data on U.S. private-sector workers, the cost of employee health insurance to employers equals about 11% of wage and salary costs.[3] We do not find a statistically significant effect on average.

Fourth, we study how the relationship between labor-market concentration and wage differs depending on the degree of product-market concentration, worker unionization, and occupational offshorability. Our novel ability to measure both labor- and product-market concentration enables this first test. We find that negative effects of labor-market concentration on wages are strengthened by greater product-market concentration. There is some evidence that presence of strong worker organizations has the opposite effect, countervailing the negative effects of labor-market concentration on labor compensation. For wages, the interaction term is positive but not significant; for employment-based health insurance coverage, it is positive and significant. Benmelech et al. (2019) used national-level unionization rates in the handful of industries they studied and found that concentration had more-negative effects in less-unionized industries. We generalize this across the whole labor market and exploit variation in occupational unionization rates across state-year. Like them, we also find evidence that unionization counteracts the negative effects of concentration. Lastly, though theory would predict a weaker negative effects of concentration on wages in more-offshorable occupations (where localness matters less), offshorability is not estimated to affect the relationship in our analysis.

2 Data

Our primary sample comes from the American Community Survey (ACS) between the years 2005 and 2014 supplemented with the 5% public-use subsample of the 2000 Decennial Census,

[3]The statistics is from `https://www.bls.gov/news.release/ecec.nr0.htm`

drawn from IPUMS-USA Ruggles et al. (2018). Let t index years.

The virtue of this sample relative to other data used in this literature is its measures of worker wage, industry, occupation, and locale at the individual level. This enables us to separately measure the degree of labor-market concentration in the workers' occupation-locale from the degree of consumer-market concentration in their industry-locale. Other papers in this line of research have not included both industry and occupation, instead focusing on one or the other, interpreted the focal variable as the labor-market boundary, and left the concentration of the other in the residual Azar et al. (2017, 2018); Benmelech et al. (2019); Berger et al. (2019); Hershbein et al. (2019); Rinz (2018). The one exception is Prager and Schmitt (2019), who focus only on a select set of occupations within one industry. Additionally, the micro-data includes measures of each worker's human-capital characteristics, which provide additional insight into mechanisms. Let i index workers in the sample.

Labor market. We define a labor market as the combination of an occupation and a commuting zone. Markets are indexed by m, with $o(m)$ and $l(m)$ denoting a market's occupation and locale, respectively.

Conceptually, occupation is superior to industry as the basis for defining a labor market. Occupation is an aspect of a job and rooted in the knowledge, skills, and abilities that workers and firms trade in the labor market. Industry is an aspect of a product and rooted in the characteristics that consumers and firms trade in goods and service markets. We use the 3-digit 1990 Census occupational codes and examine 334 occupations.

To define locales, we use the 1990 definition of commuting zones (CZ) and use all years of data for which it is available in IPUMS. IPUMS does not have information on CZ but has information on the county of an individual's residency.[4] To map each county to a CZ, we use the crosswalk from Autor and Dorn (2013).[5] This yields 62,893 distinct labor markets observed in 11 years, for a total of 403,876 possible market-years observed.

[4] The county FIPS code is not available in years 2001-2004.

[5] The crosswalk is available at `https://www.ddorn.net/data.htm`.

Labor compensation. The primary outcome measure (Y) is an employee's log hourly wage measured in 1999 dollars. We include individuals between age 16 and 64 who work in the for-profit firms in private sector. We also drop those associated with institution group quarters, and those with missing wage, 1990 census industry, 1990 commuting zone, or 3-digit 1990 census occupational codes. This leaves 7,223,866 observations of workers. Hourly wages average \$16.13 with standard deviation \$21.78 and a median of \$11.69 (Table 1: Panel A).[6]

As a supplemental measure of labor compensation, we also study whether a worker reports having employment-based health insurance (70 percent do) and how this relates to labor-market concentration. This is observed in the ACS from 2008 forward.[7]

Labor-market concentration. For each labor market-m each year-t, we measure concentration by combining data on each establishment's employment level, industry, parent firm, and location from Dun & Bradstreet (D&B) with information on the joint distribution of occupation and industry employment nationally.

The D&B's data on each establishment's location, industry, firm, ultimate parent firm, and total employment level but no data on workers' occupations has the same structural features as the Census Longitudinal Business Database used by Rinz, Benmelech et al., Berger et al., and Lipsius to measure concentration. For each establishment, D&B provides information on establishment name, firm name, D&B firm ID, location (street address, city, county, and state), 4-digit 1987 version SIC industry, which we index by d, D&B ultimate parent ID, sales, and employment. To match each SIC code to a 3-digit detailed census industry code, we use the crosswalk from the U.S. Census Bureau.[8] The county code in the

[6]To measure hourly wage, we divide annual earnings by 52 times reported usual hours per week. Weeks of work is not reported in all years so we do not use it. Results using direct data on annual, rather than constructed hourly, earnings are very similar. In the prior literature, only Rinz used individual-level wage data and he used annual earnings, lacking any measures of time worked. Others use posted wages on vacancies or establishment average wage or earnings. 2017 \$1.471 = 1999 \$1.

[7]If a person is covered by own or another family member's current employer, former employer, or union, then this person is coded covered by employment-based health insurance. https://usa.ipums.org/usa-action/variables/HINSEMP#description_section

[8]The crosswalk is available at "CPS Industry Classifications (1992-2002)" in http://unionstats.com/. For each detailed census industry code, this crosswalk provides the equivalent SIC codes, mostly at the

data is defined by D&B and we use the crosswalk provided by D&B to map each county to the FIPS county code.

To go from establishment's industry and employment to an estimate of establishment's employment by occupation, we multiply each establishment's employment level times the national occupational distribution of employment for the establishment's industry. We estimate a distribution of occupational employment by industry each year ($Pr(o)_{dt}$) from the Census microdata's joint distribution of occupation among U.S. workers in industry d in year t. For an establishment-e in industry d in year t employing E_{dte} workers, its number of employees in occupation-o is measured as $E_{ote} \equiv E_{dte}Pr(o)_{dt}$.

Multiple establishments within the same parent firm by locale combination are considered as a single employer. Each firm's employment in a market is the sum of its establishments' employment levels: $E_{mtf} \equiv \sum_{e \in f} E_{mte}$ Letting N_{mt} be the number of firms employing workers in occupation-$o(m)$ in year-t, each firm's employment share is $s_{mtf} \equiv E_{mtf}/E_{mt}$ where E_{mt} is total market employment, the sum of E_{mtf} across firms. A positive employment level is observed in 403,876 market-years.

Labor-market concentration is measured by an employment Herfindahl-Hirschman Index (EHHI) based on firms' employment shares:

$$EHHI_{mt} = \sum_{f=1}^{N_{mt}} s_{mtf}^2$$

.

Our measure of concentration very likely underestimates true concentration. If a firm in a metro has only 1 employee but it is in an industry that nationally has a positive probability of employing people in 100 occupations, the firm is measured as having a fraction of an employee in each of those 100 occupational labor-markets in that metro. This mechanically

3-digit level. For a few cases, we have to construct the crosswalk such that a group of the census industry codes is uniquely mapped to a group of SIC codes and vice versa. Specifically, we aggregate the census codes 272 and 280 as code "272,280", 371 and 372 together as code "371,372", 771 and 790 together as "771,790", and 862 and 863 together as code "862,863."

forces there to be a high number of employers in each labor market but most will have very small shares. For this reason, we recommend interpreting neither our estimate of EHHI levels nor of the number of employers literally. In our analysis of the effects of concentration, we will use market fixed effects and focus on how changes in $log(EHHI)$ predict changes in $\log(Wage)$. The essential question is whether changes in our EHHI measure capture changes in true labor-market concentration. Conceptually, it should.

This is the first economy-wide estimate of labor-market concentration based on employment shares in occupationally-defined labor markets in the recent literature.[9] Across market-years, the measured average EHHI is 0.036 (or 360 of 10,000) with standard deviation 0.074 and median 0.013, consistent with a skew towards higher concentration (Table 1).

The D&B data are not produced by required official reporting and employment and revenue measures are sometimes imputed by D&B or missing. However, D&B has been in this line of work, producing and selling such databases for decades in order to support business-to-business marketing and analysis and a variety of economic research has used these data, for instance (Alfaro and Charlton, 2009; Bitler and Haider, 2011; Levine et al., 2012; Kapadia, 2011; Bader et al., 2010; Wang and Bansal, 2012).

It is useful to compare our measures to others derived from the LBD. Figure 1 shows the trend in average of EHHI in 2000 and each year from 2005 to 2014. Rinz (2018) computes a measure of EHHI in his Figure 2 but using a different measure of labor market, industry by commuting zone instead of occupation by commuting zone. Despite these differences and our levels being consistently lower by a factor of about two-thirds, changes in our EHHI measures follow a similar path. Both Rinz's and our estimates fall steadily from 2000 until the start of the Great Recession, rise abruptly, and then fall slowly after 2012.

Eighty percent of variation in labor-market concentration across individual workers is absorbed by a set of market fixed effects and year fixed effects (Table 1:R^2). We exploit the

[9]Others have been based on vacancy shares, not employment shares (Azar et al., 2017, 2018; Hershbein et al., 2019) or labor markets defined along industrial lines (Rinz, 2018; Lipsius, 2018; Berger et al., 2019), not occupational lines.

20% of variation that remains, representing changes in labor-market concentration within labor market over years driven by local establishment entry, exit, employment growth or decline, firm merger or division, and changes in occupational shares within industry over time.

We use other important, time-varying influences on average wages that may be correlated with labor-market concentration as control variables.

Product-market concentration. A key contribution of our paper beyond the prior literature is to distinguish product-market concentration from labor-market concentration, to separately measure both, and to estimate the relationship of each to wages conditional on the other. Each worker in our Census data is observed in an occupation and an industry. Within a commuting zone, workers in the same labor market (occupation-CZ) can be in different product markets (industry-CZ).

We measure each industry-CZ-year's product-market concentration with HHI based on firms' sales shares in the industry-CZ-year constructed from the D&B establishment data on location, industry, and annual sales, aggregating up in a way parallel to that described above for labor market concentration. Our measure of product-market concentration is very similar to a recent study of product-market concentration (Rossi-Hansberg et al., 2018). They use a modified version of the D&B data, called NETS, and also use CZ as one measure of locale.

Both our labor-market and product-market HHI measures derive from the CZ-industry-year firm shares. The product-market HHI uses firms' local shares of sales (SHHI). The labor-market HHI uses firms' shares of occupational employment after projecting establishment employment into occupational employment.

To get intuition for how the EHHI and SHHI measures work, consider a simple example with four firms in a single CZ-year. As indicated in the first 2 columns of the table below, firms 1 and 2 are in industry A and firms 3 and 4 are in industry B.

In industry A, firm 1 has half the revenue of firm 2. Their revenue shares are 0.33 and 0.67, respectively, and these are used to compute SHHI equal to 0.556 for industry A in this CZ-

Simple example of measuring product- and labor-market shares

Firm	Ind.	Revenue	Share Rev. | Industry	Employees	Employees by occ. L	Employees by occ. H	Occ. empl. L-share	Occ. empl. H-share
1	A	1	0.33	1	0.6	0.4	0.28	0.10
2	A	2	0.67	2	1.2	0.8	0.57	0.21
3	B	1	0.50	1	0.1	0.9	0.05	0.23
4	B	1	0.50	2	0.2	1.8	0.10	0.46

year. In industry B, the firms have equal shares, implying industry B's SHHI is 0.50. Each firm's employment level is observed. Using the national occupational distribution conditional on industry, we project employment levels by occupation to each firm. Assume for simplicity that there are only 2 occupations, indexed L and H, and that the occupational distributions conditional on industry, $P(E^L, E^H|Ind)$, are $(0.6, 0.4|Ind = A)$ and $(0.1, 0.9|Ind = B)$. Projecting occupational employment levels to each firm, firm 1 is measured as employing 0.6 worker in occupation L and 0.4 workers in occupation H. Proportional to employment levels and using the same distribution because it is in the same industry, firm 2 employs double those levels. The same logic leads to employment measures in firms 3 and 4. Industry B tends to employ a higher share of workers in occupation H than industry A does so, even though firms 1 and 3 have the same overall employment level, they have different measured occupational employment. This would yield EHHI equal to 0.419 for occupation L, where firm 2 tends to dominate and firm 3 has a small share of employment, but 0.319 in H, the labor market with less-concentrated employment. This measurement strategy is designed to leverage available data in a sensible way and capture independent variation in EHHI across occupations, distinct from SHHI. We execute this across 198 industries, 334 occupations (3-digit 1990 Census codes), 223 commuting zones and 11 years.

Workers are in local industries with an average SHHI of 0.230 (2,300 out of 10,000). The median SHHI is 0.122, consistent with a skew towards high concentration, and standard deviation is 0.260.[10] Figure 1 shows that the trend in workers' average SHHI also declines

[10] In our sample, SHHI is missing for around 0.6% of observations at the product market-year level. We impute these as equal to 0 and include an indicator for missing.

leading up to the Great Recession and rises after, although the post-recession growth in SHHI makes up a lower share of the pre-recession fall in SHHI than it did for EHHI. Rossi-Hansberg also estimates SHHI with a very similar dataset and very similar definitions. Reassuringly, we obtain very similar results. Both of our trends fall between 2000 and 2010, then increase until 2013. In 2014, theirs steadily continues its modest increase but ours dips a bit.

On one hand, EHHI and SHHI are positively correlated, creating a risk of omitted variable bias when EHHI is analyzed without controlling for SHHI. On the other hand, are they too-highly correlated to be sensibly separated? To understand the covariation in these variables that will be relevant in the regression analysis, we regress logs of each at the worker level on labor market fixed effects and year fixed effects, create residuals of each, and study their relationship. The bin scatter in Figure 2 shows that, as expected, a positive association exists. Both EHHI and SHHI depend on the number and sizes of local firms. However, because they focus on different markets (labor versus product or, equivalently, occupation versus industry) a lot of independent variation remains. Conditional on labor market and year, residuals of log(EHHI) and log(SHHI) have a simple pairwise correlation of only 0.041 across workers.

Other market controls. Changes in wages may also be related to changes in employment levels. The sign depends on whether the changes are due to supply or demand shocks. We are not focused on this factor but construct and control for a time-varying measure of log total employment by market-year using our occupational employment projections. The average market has 3,221 employees with a median of 882 (Table 1: Panel A). Lipsius (2018) also conditions on employment levels too, arguing that it is a proxy for labor productivity.

Other studies in this literature, with the exception of Benmelech et al. (2019), do not include any direct measure of labor productivity. Benmelech et al focus only on manufacturing primarily because they have a measure of establishment-year labor productivity in this sector and can link to establishment-year average wage. This is a very nice feature of their study, as labor productivity may lift wages. Though we cannot do as well as this, we can do better than most. We begin by measuring labor productivity as the ratio of sales to employees at the establishment-year level. However, we don't know which establishments employ the workers whose wages we observe so we average up establishment-year labor productivity to the product-market-year level and use this as a control in some specifications tied to each worker's local industry, i.e. product market. Labor productivity averages \$70,470 per employee with a standard deviation of \$47,191.[11]

Worker characteristics. The Census data provide linking of individual worker's wages to their demographic characteristics, in particular age, education level (coded as at least a bachelors degree or not), an indicator for missing education value, birthplace (coded as U.S. born and non-U.S. born), an indicator for missing birthplace information, gender, race (coded as white, black, and other), ethnicity (coded as non-Hispanic and Hispanic), and marital status. These are important determinants of wages and potential confounders or mechanisms in the relationship between labor-market concentration and wages. Controlling for observable differences across labor markets in workforce composition as a potential confounding explanation for wage differences, adding to the credibility of the estimated effects of labor-market concentration.

Specifications. We estimate the following regression at the individual worker level:

$$Y_{mti} = \beta \log(EHHI_{mt}) + \alpha X_{mti} + \gamma_t + (\gamma_{0m} + \gamma_{1m} t) + \epsilon_{mti}$$

where Y_{mti} is the natural log of the individual worker's real hourly wage and salary income or a dummy variable indicating whether a worker is covered by employer-sponsored health insurance, $\log(EHHI_{mt})$ is the natural logarithm of the labor-market's employment concentration in that worker's occupation-CZ-year, and X_{mti} contains various observable characteristics of the worker and the market-year. All models also include year fixed effects, labor-market-specific fixed effects, and market-specific linear time trends. ϵ_{mti} is the idiosyn-

[11] We winsorize labor productivity to the 1st and 99th percentiles across all establishments in each year before averaging up to the product-market-year level.

cratic residual. Various additional fixed effects that further partition ϵ will be introduced as results are discussed. All estimations are weighted by the worker's personal weights.[12] Standard errors are clustered at the labor market level. Assuming that changes in labor-market concentration are mean independent of changes in average unobserved influences on wages (ϵ) conditional on X identifies the parameters in OLS models.

Omitted-variable bias may make OLS estimates misleading, reflecting the influence of time-varying unobservable factors that drive both changes in wages and changes in labor-market concentration. For instance, a positive productivity shock to a local firm could cause quick employment growth and increase concentration, product-market rents, and wages if workers get a constant share of rents. Further, compositional changes in the set of employing firms across the business cycle could create confounds. For instance, when lower-productivity, lower-wage firms exit during an economic contraction, concentration would increase and average wages rise.

We focus on evidence from instrumental-variables identification, closely following strategies in the prior literature (Azar et al., 2017; Rinz, 2018). Our instrument for labor-market concentration in each market-year $log(EHHI_{mt})$ is the average of the natural log of the reciprocal of the number of firms in that same occupation-year in all other commuting zones Azar et al. (2017). The instrument averages -8.22 with median -8.47 and standard deviation 0.91.[13]

This IV focuses on changes in local labor-market concentration driven by changes in the extent to which that type of labor market tends to be concentrated, rather than changes in that particular market. If other markets' average number of employing firms rises, the instrument falls. This instrument is designed to focus on the variation deriving from changes in the fundamentals of the occupation, apart from idiosyncratic changes in local market concentration that could be confounded with idiosyncratic unobserved influences on local

[12]Variable "perwt" in the IPUMS data.

[13]This level implies high numbers of employers per market, an artifact of our strategy for measuring occupational employment. The essential element is that it captures meaningful variation across time and markets.

wages. For instance, suppose adoption of a new technology makes a particular occupation more productive or national consumer tastes shift so as to increase demand for that occupation's services. Then, the number of firms employing workers in that occupation will tend to increase in many markets around the country and the instrument's value will fall in every market. OLS identification based on changes in local labor-market concentration driven by unmeasured local productivity or demand shocks would produce omitted-variable bias. However, identification based on changes in local labor-market concentration driven by changes that are not specific to the local market should be more insulated from this threat. As Azar et al. (2017) discuss, studies commonly use these kinds of leave-this-market-out instrument to deal with endogeniety of local prices (Nevo, 2001; Autor et al., 2016).

In IV analysis, our ability to control for local product-market concentration add credibility above the prior IV literature, reducing the risk of an exclusion-restriction violation. The instrument is a function of the average number of firms employing workers in that occupation in other locales. The exclusion restriction requires that this doesn't affect wages in any unobservable way; it only affects wages through labor-market concentration. Conditioning on production-market concentration pulls this potentially correlated channel of influence into observability, reducing a threat to the IV's validity.

3 Results

We begin by presenting simple, bivariate evidence using long first-differences to understand the relationship between changes in labor-market concentration and wages within labor markets over time. For each labor market, we compute the change in average log(wage) between the first year in our data, 2000, and the last year, 2014, versus the same kind of change in log(employment HHI). The top panel of Figure 3 displays a bin scatter of the result along with an estimated best-fit line. Labor markets where concentration increases more tend to experience *smaller decreases* in real wages, with a positive estimated relationship.

The bottom panel displays results from a parallel exercise with the base year 2005 and produces similar results. This results is similar to panel (d) of Rinz's Figure 21 and contrary to the expected sign. Increasing concentration could, theoretically, lead to higher wages if expectations of lower turnover led to increased investments by the workers and firms in the relationship and, for some reason, the firm shared its value with the workers despite the reduction in competition between employers (Acemoglu and Pischke, 1998; Benson, 2013).

The next section introduces the basic specifications we use and estimation results for wages under OLS. The following section discusses the analogous IV results. As in Rinz, the results differ substantially between OLS and IV. For subsequent outcomes, we focus on IV results and put OLS results in the appendix.

OLS. To begin, we look only at changes within market over time without controlling for other observables. Point estimates suggest that increases in labor-market concentration have a positive effect on wage changes, as expressed in the 0.003 point estimate with a 95% confidence interval (CI) of (0.001,0.005). This specification includes only year fixed effects, labor market (occupation-CZ) fixed effects, and labor-market-specific linear time trends (Table 2: Panel A: Specification 1). This estimated effect is very small. Moving a labor market's concentration up a standard deviation (0.074) from the mean level of concentration (0.036) is estimated to raise wages less than one percent.[14]

The basic result is robust to allowing for very aggressive sets of fixed effects. Allowing CZ-specific annual wage shocks by replacing the year fixed effects with CZ-year fixed effects raises the estimate very slightly to 0.005 (Table 2: Panel A: Specification 2). Adding the possibility of national occupation-year specific wage shocks returns the estimate to 0.003 (Specification 3). This specification is more aggressive than the prior literature. Allowing the possibility of national industry-year specific wage shocks in addition to CZ-year and occupation-year shocks (Specification 4) yields a point estimate of 0.002 with a CI of (0.00,0.004).

Each additional panel in Table 2 adds a set of observable control variables while main-

[14] $exp(0.003 \times [ln(0.036 + 0.074) - ln(0.036)]) - 1 = 0.34\%$.

taining the same structure of fixed effects across specifications.

Panel B presents estimates after adding controls for time-varying labor-market observables beyond EHHI, specifically log(average labor productivity) in the labor market, an indicator for the few markets where all establishments are missing productivity, a market-specific measure of the share of establishments missing the productivity measure, and log(total employment) in the labor market to capture changes in workforce size. Adding these controls changes the estimated labor-market concentration results just a little. Most coefficients fall and become statistically insignificant, but the basic pattern of null or small positive effects is stable.

Panel C adds each worker's local industry's product-market concentration measure, log(Sales HHI), as well as an indicator of the few cases when this is missing. Coefficients on labor-market concentration again fall and are statistically significant only in specification 2. Coefficients on product-market concentration are positive, consistent with firms sharing some product-market rents with their workers. In the OLS analysis, adding a control for the otherwise omitted local product-market concentration does slightly diminish the small estimated effect of labor-market concentration further.

IV. We reproduce the same structure as the OLS results described above except instrumenting for log(EHHI). Because the instrumental variables are almost at the occupation-year level, we do not include those corresponding fixed effects in these estimations. The instrument is strong (Appendix Table A.1).

Table 3 presents the 2SLS estimates, which suggest that higher labor-market concentration substantially reduces wages. Panel A presents results based on just the various sets of fixed effects and labor-market specific trends, without observable controls. Specification 1 looks at changes across years within labor market beyond a linear trend in unobservables and finds a -0.125 effect with a CI of (-0.192,-0.058). That point estimate implies that labor-market concentration one standard deviation above the mean is associated with 13 percent lower wages than mean concentration.[15] The estimated effect remains substantially similar using more-aggressive sets of fixed effects across the columns of Panel A. In panel B, adding market-level controls reduces the estimate effects but they remain substantial and significant. In panel C, adding product-market concentration as a control only slightly affects the estimates, which range from -0.059 with a CI of (-0.102,-0.016) in specifications 1 and 2 to -0.110 with a CI of (-0.157,-0.063) in specification 3 with implied estimated from a one-standard deviation concentration increase of -6.4% and -11.6% effects on wages, respectively.

A concern with this kind of IV that was not addressed in prior work with IVs (Azar et al; Rinz) is that a positive national-level consumer demand shock that raises labor demand for an occupation could directly drive up labor compensation and drive down labor-market concentration in every CZ for that occupation. As a result, the exclusion restriction could be violated. To mitigate this concern, we further control for the natural logarithm of total sales at the occupation-year level in the estimations.[16] We present these results in Appendix Table A.2, which is analogous to Table 3 but for the addition of this control. The estimated labor-market concentration effects are similar. However, creating some doubt about the validity of this exercise, the estimated effects of changes in occupation-year sales on wages are negative, substantial and significant. This contradicts our expectation that this proxies for a positive demand shock and would raise wages.

Employment-based health insurance. The Census also contains data on workers' coverage under employment-based health insurance since the year 2008. IV estimates do not suggest an average effect of concentration on this nonwage component of labor compensation (Table 4).[17]

Worker education level. To help understand what drives the observed negative rela-

[15] $1 - exp(-0.125 \times [ln(0.036 + 0.074) - ln(0.036)]) = 13.0\%$

[16] To measure total sales at the occupation-year level, we use the establishment-level sales information from D&B and the annual joint distribution of occupation and industry employment nationally from the Census samples, apportioning sales value across occupations within establishment based on employment share and then totalling across establishments within occupation-year.

[17] Although we do not discuss them in the text, for this table and all 2SLS estimates in the rest of the paper, appendix tables report first-stage estimates, estimates of all control-variable coefficient estimates, and OLS analogue estimates for interested readers.

tionship between concentration and average wages, it is valuable to distinguish a few potential mechanisms that might occur in a market with increasing concentration. First, it could be that workforce composition stays the same but wage growth turns negative or slows relative to what would have happened if concentration had not increased. Reducing wage conditional on worker type is what papers in the literature have tended to consider, although they have not usually measured or controlled for worker type. An exception is Rinz, that estimated effects of concentration within race, within gender, and within education group. However, neither Rinz nor others offered evidence on a second mechanism: employers' reduced wage offers (relative to the counterfactual if concentration had not increased) could lead incumbent workers with better outside options to leave and could push some potential workers never to accept offers in that market though they would have otherwise. Each would reduce average observed wages. If each worker is trapped in a market, we would expect only the first mechanism to operate. Otherwise, we might see both.

To generate evidence on the extent to which changes in concentration cause changes in the composition of the workforce, we conduct the same kind of analysis as above but using an indicator for whether each worker has at least a bachelor's degree as the outcome instead of wage or employment-based health insurance. IV estimates suggest that workers in labor markets with a one-standard-deviation greater concentration from the sample mean are about 3.8 percentage points less likely to have at least a bachelor's degree (Table 5, Panel C, Specification 3). This is suggestive evidence that a sorting process towards workers with less formal education could be part of how greater concentration yields lower labor compensation.

To illuminate this mechanism further, in Table 6, we report IV estimates adding the vector of workers' individual characteristics as predictors to our richest prior models. Adding human capital characteristics reduces the magnitude of the negative estimated labor-market concentration effect on wage from -0.11 (SE=0.024) (Tables 3: Panel C: Column 3) to -0.068 (SE=0.020) (Table 6: Column 1), consistent with increased concentration inducing negative sorting of workers into the occupation (or positive sorting out) and the point estimates would suggest this accounts for about a third of the wage reduction effect. The other two-thirds presumably comes from reductions in wage conditional on worker characteristics. Adding worker characteristics does not appear to change the estimated average impact of concentration on the probability of employment-based health insurance coverage, -0.050 (SE=0.034) in Column 2 versus -0.046 (SE=0.034) (Table 4:Panel C: Column 3).

In their analysis of job vacancy text posted by employers, Hershbein et al. (2019) found evidence of higher employer demand for higher-skill workers in more-concentrated labor markets controlling for broad occupation. Our results suggest that this employer stated-preference for higher skill, in the context of lower wages, does not translate into a more-educated workforce. It is consistent with employers asking for more of what they like on two margins, lower wages and higher skills, but having the former dominate.

Finally, we provide evidence on whether the effect of concentration on the share of workers with a bachelors degree remains important controlling for changes in other worker characteristics. This focuses on just the first It does -0.027 (SE=0.012) (Column 3) versus -0.034 (SE=0.012) (Table 5: Panel C: Column 3). We focus on worker education as the single marker of worker type that concentration might affect because it is a clear measure of human capital, productivity, and a strong wage determinant. However, many other characteristics are correlated with education level and wage, such as age and race. Though sorting could occur on these as well, sorting on education appears to play a role.

3.1 Heterogeneous effects

We examine if the effects of labor-market concentration differ depending on the levels of each of three factors: local product-market concentration, worker unionization rate, and occupational offshorability. We use only the richest specification (as in Table 3: Panel C: Column 3) and instrument for labor-market concentration and its interaction with our measures of each of these factors in turn.

For both wages (Panel A) and employment-based health insurance probability (Panel B), labor-market concentration has a more negative effect on labor compensation in the context of more-concentrated product markets than less-concentrated product markets (Table 7: Column 1). Any greater product-market rents within the firms driven by increased product-market concentration do not seem to translate into higher labor compensation and especially not in the context of greater labor-market concentration.

In manufacturing, Benmelech et al found evidence that stronger unions reduce the negative effect of labor-market concentration on wages, consistent with unions increasing worker bargaining power and protecting against negative compensation effects from concentration's limiting of workers' outside options. We broaden the analysis to the whole private sector, leverage different variation in unionization rates, and find similar results. Because the Census does not measure worker's union status, we rely on the Current Population Survey. To get enough observations per cell, we aggregate occupations up into 6 broad groups and estimate unionization rates within each group-state.[18] For each study year, we pool CPS observations in that group-state across a five-year window centered on the study year and use CPS earner weights to estimate a unionization rate.[19] We match this back to each Census worker whose wages we are explaining based on occupation-state-year. Our estimated coefficients on the interaction between labor market concentration and unionization rate for wage and employment-based health insurance coverage are both positive but only the latter is significant. This is consistent with evidence that unions have a larger proportional effect on compensation in fringe benefits than in wages (Knepper, 2018).

The IV point estimates suggest that moving from a labor market with a mean unionization rate (7.4%) to a market with a unionization rate one standard deviation higher (14.8%) does mitigate the effect of concentration on labor compensation. Although the implied mitigation

[18]We follow broad groups in Census 1990 at IPUMS: "Managerial and professional specialty occupations", "Technical, sales, and administrative support occupations," "Service occupations," "Farming, forestry, and fishing occupations," "Precision production, craft, and repair occupations," and "Operators, fabricators, and laborers."

[19]Benmelech et al used national-level industry-specific unionization rates. We use state-level, occupation-group-specific unionization rates.

of the negative wage effect of concentration is minor and not significant (from -0.109 to -0.104), higher unionization is estimated to significantly mitigate the negative marginal effect of *log(EHHI)* on the employment-based health insurance coverage probability from -0.045 to -0.018 holding concentration fixed. This implies a 4% increase from the observed coverage share. This is on top of direct effects of unionization on compensation.

Finally, we test whether occupational offshorability changes the effect of labor-market concentration, measuring offshorability following Autor and Dorn (2013). For more-offshorable occupations, locale is a less-meaningful labor market boundary and $log(EHHI)_{mt}$ a noisier measure of concentration. Therefore, we expected a negative main effect of concentration and a positive interaction term. Instead, we estimate a negative main effect of concentration but a null interaction term with offshorability for both wages and health insurance.

4 Conclusion

We develop new evidence that recent results linking higher labor-market concentration to lower wages are robust to potential confounders such as product-market concentration, labor productivity, and labor force composition. OLS estimates imply null or small, positive effects but, as in Azar et al. (2017) and Rinz (2018), analysis using a market-type's average market structure in other locales as an instrument for each local market's concentration yields estimates that are substantially larger, significant, and negative.[20] For a rough sense of magnitude, reducing concentration of a labor market by a standard deviation (0.074) to the mean level (0.036) would imply a 13.1 percent increase in wages (based on Table 3: Panel C: Column 3 estimate).

In terms of changes in labor-market concentration as an explanation for recent *changes* in U.S. wages, the potential import is limited by the fact that average concentration has not changed much. As a back of the envelope, the move from the maximum average annual

[20] Rinz (2018) does not present OLS results, focusing only on the IV. However, his figure 21(d) is a visual analogue to OLS with worker-level wage data and also describes a weak positive association between concentration and wages.

concentration level (0.05 in 2000) to the minimum (0.035 in 2008) would imply a predicted 4.0 percent increase in wages and, then, a 1.5 percent wage decrease as concentration moved to 0.04 in 2014. This aligns with results in Rinz (2018), Lipsius (2018), and Hershbein et al. (2019) suggesting that changes in labor-market concentration cannot do much work explaining changes in labor share. However, the results suggest concentration has been a factor consistently depressing wages across the period.

Comparing our estimates to those of Rinz (2018), the most-similarly specified, is particularly illuminating. We both define locale as commuting zone and have similar underlying data and analytic structures. He uses the LBD and defines labor markets along local industrial lines. We use the similarly-structured D&B data combined with national occupational distributions for each industry to measure labor-market concentration along local occupational lines while controlling for local product-market concentration. The most-comparable estimates are between his richest model in the 2005-2015 period (Tables 5: Column 5) and our model with industry-year effects but excluding market-level controls and product-market concentration (Table 3, Panel A, Specification 2). All include market fixed effect, market trends, and locale-year fixed effects. Our estimated -0.124 (SE=0.034) is very similar to his -0.134 (SE=0.028). When we add market-level and product-market concentration controls (Panel C), our estimate falls to -0.059 (0.022), suggesting that omitting these factors may lead to overestimation of the labor-market concentration effect. However, when we add industry-year fixed effects, the estimate strengthens to -0.110 (0.024), back to a magnitude similar to Rinz's.[21]

We add novel evidence that the negative effect of labor-market concentration on wage is robust to conditioning on local product-market concentration, a theoretically-important, potential confounder. Increases in workers' local product-market concentration predicts increased wages, consistent with rent-sharing within the firm. However, labor-market concentration estimates barely change when product-market concentration is added as a control.

[21] Estimates from other papers do not include market-specific trends. A working paper version of our paper available at SSRN presents estimates without these trends.

The estimated effect on the probability of employer-provided health insurance is in the same direction but not significant on average.

This happens both by reducing the average human capital level of workers employed in the market and reducing the compensation of workers conditional on their human-capital levels. Including individual worker human capital measures diminishes the labor-market concentration estimate by about a third. Greater concentration tends to lower the share of workers with at least a bachelor's degree, a finding that enriches the story in Hershbein et al. (2019). While vacancy postings by employers in more-concentrated markets may express a desire for higher skills and lower wages, it seems in practice that they hire people with lower education levels and at lower wages. Higher product-market concentration strengthens the negative effect of labor-market concentration. On the other hand, there's some weak evidence that stronger unions counteract negative effects labor-market concentration on labor compensation.

This evidence suggests reductions in labor-market concentration could lift labor compensation levels substantially towards competitive levels. Marinescu and Hovenkamp (2018) and Naidu et al. (2018) have recently fleshed out applications of traditional legal and economic anti-trust analysis into the labor market. In labor markets with employer market power derived from concentration and other sources (information frictions, mobility costs, legal barriers...), labor market power in the form of stronger workers' organizations can countervail and shift the balance of bargaining power (Lee and Mas, 2012; Sojourner et al., 2015). In theory, this can increase labor-market efficiency in some cases. Blunting employer market power is possible through tools beyond traditional anti-trust enforcement as well: reducing covenants not to compete and no-poach agreements (Krueger and Posner, 2018; Starr, 2019), addressing workers' information problems with respect to unobserved employer heterogeneity (Benson et al., 2019), setting labor-market standards through regulation (Shierholz, 2018). Where concentration suppresses labor compensation, these kinds of reforms are likely have larger benefits and smaller costs.

References

Acemoglu, Daron and Jörn-Steffen Pischke, "Why do firms train? Theory and evidence," *The Quarterly Journal of Economics*, 1998, *113* (1), 79–119.

Alfaro, Laura and Andrew Charlton, "Intra-industry foreign direct investment," *American Economic Review*, 2009, *99* (5), 2096–2119.

Autor, David and David Dorn, "The growth of low-skill service jobs and the polarization of the US labor market," *American Economic Review*, 2013, *103* (5), 1553–97.

Autor, David H, David Dorn, and Gordon H Hanson, "The china shock: Learning from labor-market adjustment to large changes in trade," *Annual Review of Economics*, 2016, *8*, 205–240.

Azar, José A, Ioana Marinescu, Marshall I Steinbaum, and Bledi Taska, "Concentration in US labor markets: Evidence from online vacancy data," Technical Report, National Bureau of Economic Research 2018.

Azar, José, Ioana Marinescu, and Marshall I Steinbaum, "Labor market concentration," Technical Report, National Bureau of Economic Research 2017.

Bader, Michael DM, Marnie Purciel, Paulette Yousefzadeh, and Kathryn M Neckerman, "Disparities in neighborhood food environments: Implications of measurement strategies," *Economic geography*, 2010, *86* (4), 409–430.

Benmelech, Efraim, Nittai Bergman, and Hyunseob Kim, "Strong employers and weak employees: How does employer concentration affect wages?," Technical Report, National Bureau of Economic Research 2019.

Benson, Alan, "Firm-sponsored general education and mobility frictions: Evidence from hospital sponsorship of nursing schools and faculty," *Journal of Health Economics*, 2013, *32* (1), 149–159.

_ , Aaron Sojourner, and Akhmed Umyarov, "Can Reputation Discipline the Gig Economy?: Experimental Evidence From an Online Labor Market," *Management Science*, 2019.

Berger, David W, Kyle F Herkenhoff, and Simon Mongey, "Labor Market Power," Technical Report, National Bureau of Economic Research 2019.

Bitler, Marianne and Steven J Haider, "An economic view of food deserts in the United

States," *Journal of Policy Analysis and Management*, 2011, *30* (1), 153–176.

Hershbein, Brad, Claudia Macaluso, and Chen Yeh, "Concentration in U.S. Local Labor Markets: Evidence from Vacancy and Employment Data," 2019.

Kapadia, Nishad, "Tracking down distress risk," *Journal of Financial Economics*, 2011, *102* (1), 167–182.

Knepper, Matthew, "From the Fringe to the Fore: Labor Unions and Employee Compensation," *Review of Economics and Statistics*, 2018.

Krueger, Alan and Eric Posner, "A Proposal for Protecting Low-Income Workers from Monopsony and Collusion," *The Hamilton Project Policy Proposal*, 2018, *5.*

Lee, David S and Alexandre Mas, "Long-run impacts of unions on firms: New evidence from financial markets, 1961–1999," *The Quarterly Journal of Economics*, 2012, *127* (1), 333–378.

Levine, David I, Michael W Toffel, and Matthew S Johnson, "Randomized government safety inspections reduce worker injuries with no detectable job loss," *Science*, 2012, *336* (6083), 907–911.

Lipsius, Ben, "Labor Market Concentration Does Not Explain the Falling Labor Share," Technical Report, University of Michigan Department of Economics 2018.

Manning, Alan, "Imperfect competition in the labor market," in "Handbook of labor economics," Vol. 4, Elsevier, 2011, pp. 973–1041.

Marinescu, Ioana Elena and Herbert Hovenkamp, "Anticompetitive Mergers in Labor Markets," 2018.

Naidu, Suresh, Eric A Posner, and E Glen Weyl, "Antitrust Remedies for Labor Market Power," 2018.

Nevo, Aviv, "Measuring market power in the ready-to-eat cereal industry," *Econometrica*, 2001, *69* (2), 307–342.

Prager, Elena and Matthew Schmitt, "Employer consolidation and wages: Evidence from hospitals," *Washington Center for Equitable Growth Working Paper*, 2019.

Rinz, Kevin, "Labor Market Concentration, Earnings Inequality, and Earnings Mobility," Technical Report, U.S. Census Bureau Center for Administrative Records Research and Applications

2018.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Nicholas Trachter, "Diverging trends in national and local concentration," Technical Report, National Bureau of Economic Research 2018.

Ruggles, Steven, Josiah Grover Erin Meyer Jose Pacas Sarah Flood Ronald Goeken, and Matthew Sobek, "IPUMS USA: Version 8.0 [dataset]," Minneapolis, MN 2018.

Shambaugh, Jay and Ryan Nunn, *Revitalizing Wage Growth: Policies to Get American Workers a Raise*, The Hamilton Project, 2018.

_ , _ , Patrick Liu, and Greg Nantz, "Thirteen Facts about Wage Growth," 2017.

Shierholz, Heidi, "Strengthening Labor Standards and Institutions to Promote Wage Growth," *The Hamilton Project*, 2018, *23.*

Sojourner, Aaron J, Brigham R Frandsen, Robert J Town, David C Grabowski, and Min M Chen, "Impacts of unionization on quality and productivity: Regression discontinuity evidence from nursing homes," *ILR Review*, 2015, *68* (4), 771–806.

Starr, Evan, "The Use, Abuse, and Enforceability of Non-Compete and No-Poach Agreements," 2019.

Wang, Taiyuan and Pratima Bansal, "Social responsibility in new ventures: profiting from a long-term orientation," *Strategic Management Journal*, 2012, *33* (10), 1135–1153.

Figure 1: Employment and Sales HHI Trends

This figure reports the employment and sales HHIs trends. The statistics are calculated using all firms in D&B database. We calculate average employment HHI across labor markets and average sales HHI across product markets each year using employment-weights. The sample years include 2000 and 2005-2014. A labor market is defined as the interaction between an occupation (1990 Census definition at the 3-digit level) and a commuting zone (1990 definition). A product market is defined as the interaction between an industry (based on 3-digit 1990 Census definition) and a commuting zone (1990 definition).

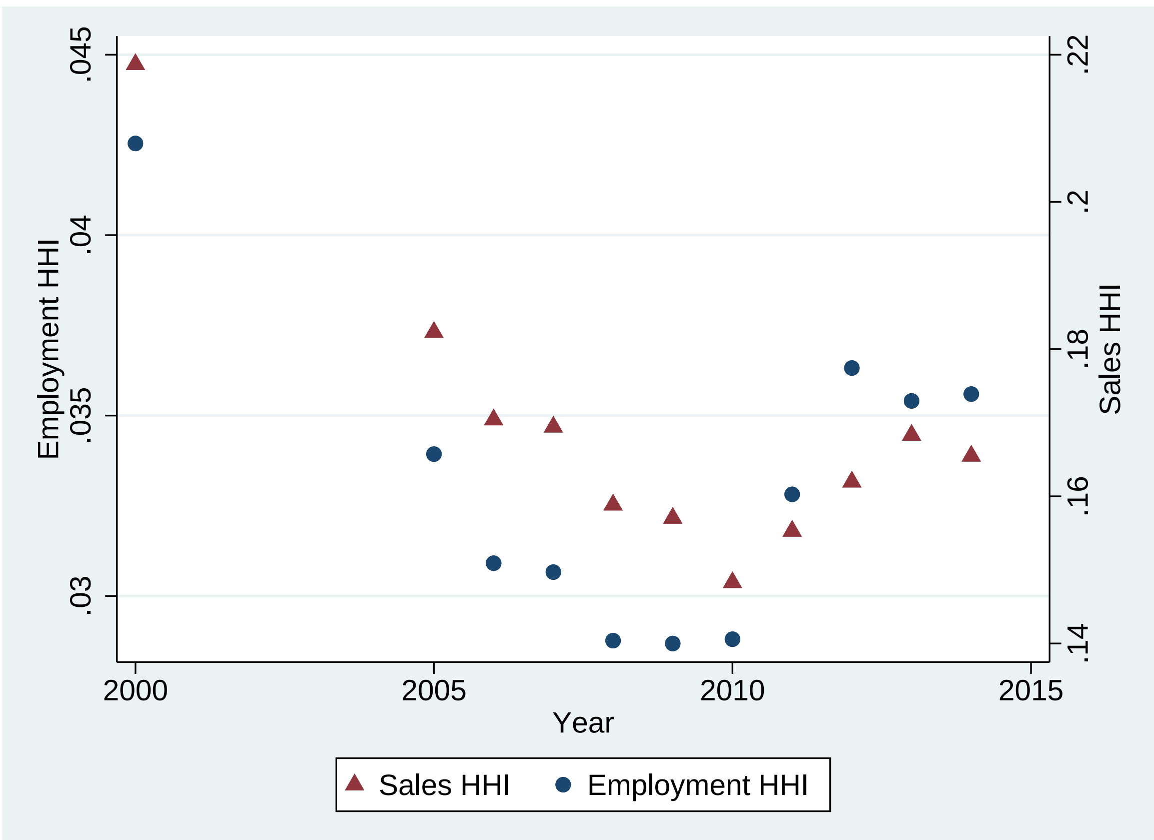

Figure 2: Residual of Log(Employment HHI) on Residual of Log(Sales HHI)

This figure reports the relation between the residualized log(Employment HHI) and the residualized log(Sales HHI). The residualized log(Employment HHI) is computed at the individual level and conditional on the labor market and year fixed effects. The residualized log(Sales HHI) is computed at the individual level and conditional on the product market and year fixed effects.

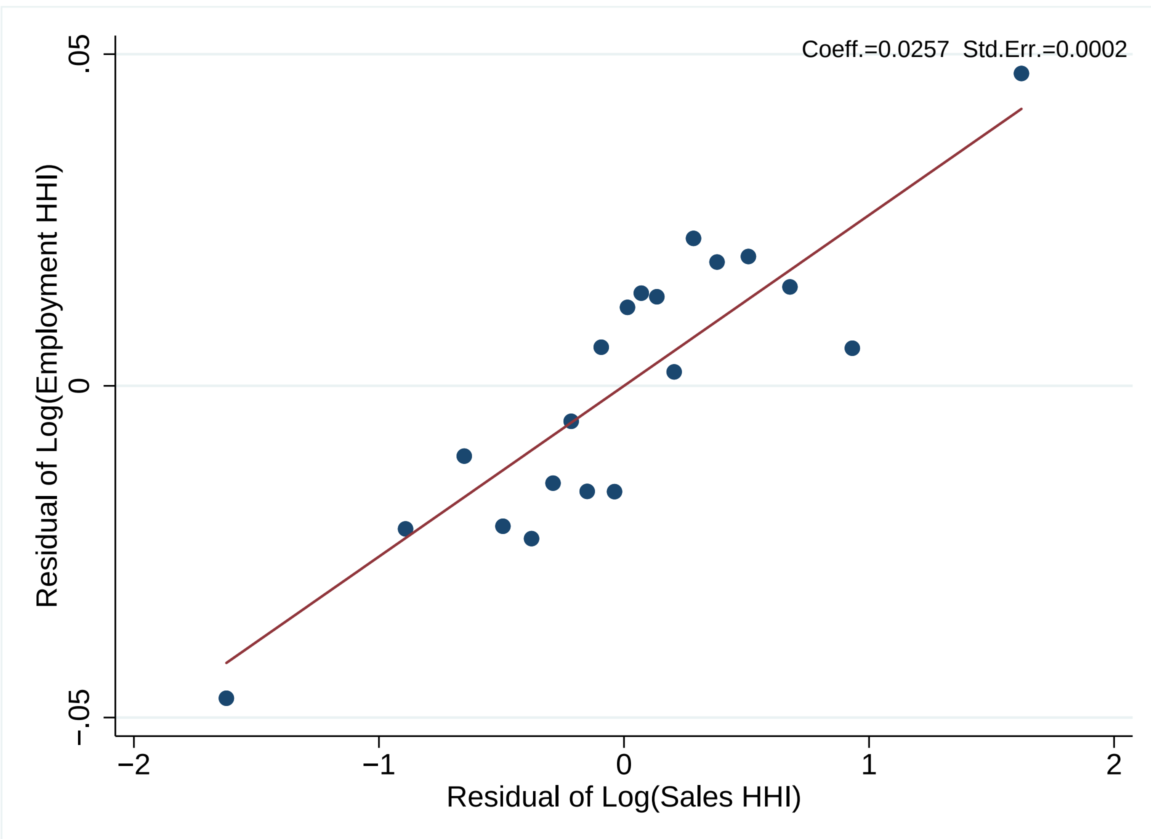

Figure 3: Change in Log(Mean Hourly Wage) on Change in Log(Employment HHI)

This figure reports the relationship between changes in concentration and wages within labor markets over time using long first-differences. In the top panel, for each labor market, we compute the change in average log(hourly wage) and in log(employment HHI) between 2000 and 2014. In the bottom panel, we use the year 2005 as the base year and perform a parallel exercise as in the top panel.

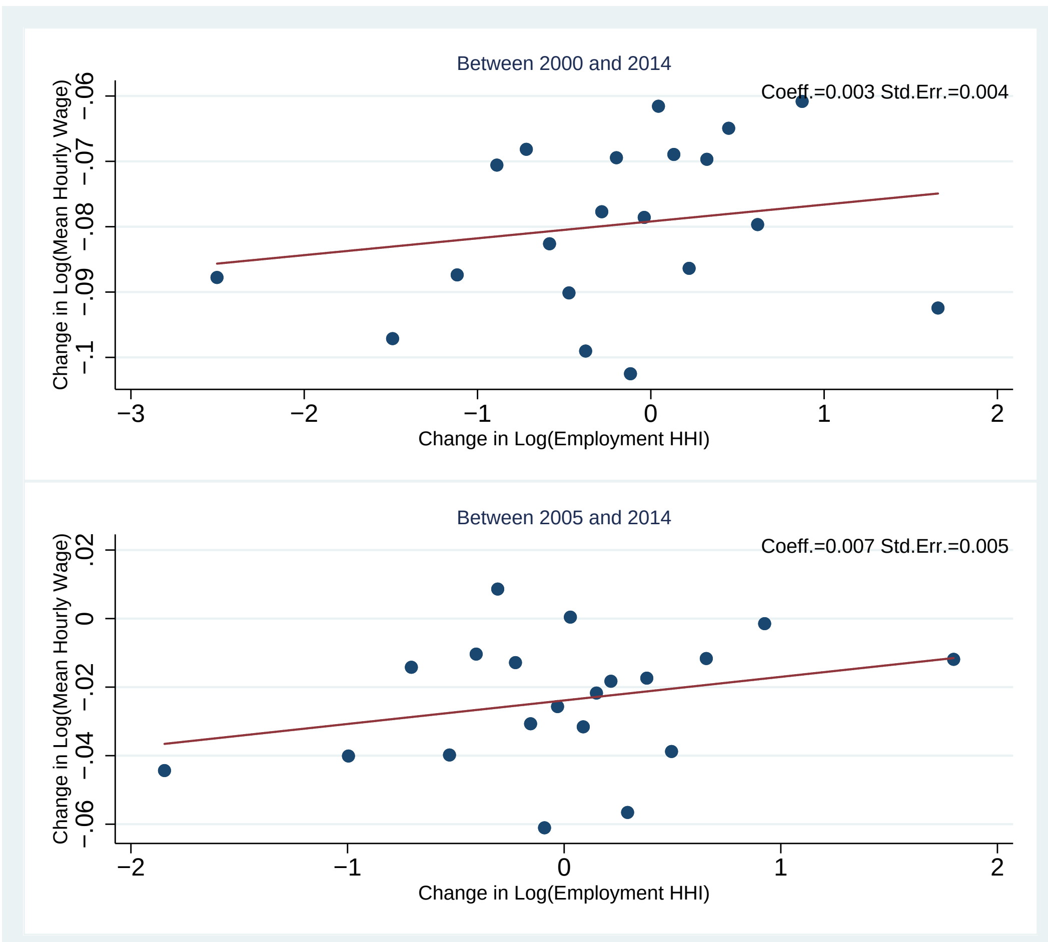

Table 1: **Summary Statistics**

This table reports the summary statistics of variables used in the estimations. A labor market is defined as the interaction between 3-digit 1990 census occupation (OCC) and a 1990 commuting zone (CZ). A product market is defined as the interaction between an industry, which is derived from 3-digit 1990 census industry, and a CZ. For employment HHI, the instrumental variable, and total employment, they are defined at the labor market-year level. For sales HHI and variables related to labor productivity, they are defined at the product market-year level. For each CZ-OCC-year cell, the *Instrumental variable* for employment HHI is the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in that year. There are 7,223,866 individuals, 403,876 CZ-OCC-year, and 286,303 CZ-industry-year observations in the sample. The bachelor degree dummy and U.S. born dummy are missing for 0.8% and 1.1% of individuals, respectively. Labor productivity is missing for 0.6% of CZ-industry-year observations. *Health Insurance through Employers/Unions* is available since 2008 in the ACS and we have data for 3,536,391 individuals. *Unionization Rate* is the 5-year average unionization rate in a major occupation group-state cell centered around a year in CPS. It is available for 2,886 OCC-state-year observations. *Offshorability* measures the extent to which the tasks performed by occupations are offshorable and the data is from David Dorn's webpage and it is available for 322 occupations derived from the 3-digit 1990 census occupation codes. The last column reports the R^2 from regressing each variable on labor/product market and year fixed effects at the individual level. The hourly wage and labor productivity are in the year 1999 dollars.

	Mean	Std.Dev.	P10	Median	P90	R^2
Hourly Wage	16.126	21.775	3.721	11.688	31.033	0.193
Employment HHI	0.036	0.074	0.002	0.013	0.085	0.801
Sales HHI	0.230	0.260	0.015	0.122	0.647	0.804
Sales HHI Missing	0.006	0.075	0.000	0.000	0.000	0.662
Labor Productivity ($000)	70.470	47.191	31.509	59.656	117.790	0.790
Fraction of Missing Estab Labor Productivity	0.328	0.268	0.019	0.267	0.740	0.892
Employment in D&B (000)	3.221	9.163	0.124	0.882	7.031	0.988
Age	38.370	12.466	22.000	38.000	56.000	0.127
Male	0.552	0.497	0.000	1.000	1.000	0.327
Black	0.119	0.324	0.000	0.000	1.000	0.148
Other Race	0.172	0.377	0.000	0.000	1.000	0.145
Married	0.498	0.500	0.000	0.000	1.000	0.091
Hispanic	0.203	0.402	0.000	0.000	1.000	0.298
US Born	0.759	0.427	0.000	1.000	1.000	0.219
Full-time Job	0.741	0.438	0.000	1.000	1.000	0.221
Bachelor Degree	0.281	0.449	0.000	0.000	1.000	0.361
Instrumental Variable	-8.223	0.906	-8.969	-8.468	-7.174	0.890
Health Insurance through Employers/Unions	0.701	0.458	0.000	1.000	1.000	0.188
Unionization Rate	0.074	0.074	0.007	0.049	0.190	
Offshorability	0.009	1.305	-1.745	0.011	1.680	

Table 2: **Effect of labor-market concentration on hourly wage using OLS**

The dependent variable in all estimations is worker's *Log(Hourly Wage)*. All estimations are weighted by the worker's personal weight. There are 7,223,866 individuals in the sample. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects			
	(1)	(2)	(3)	(4)
Log(Employment HHI)	0.003**	0.005***	0.003**	0.002
	[0.001]	[0.001]	[0.001]	[0.001]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.339	0.340	0.340	0.370

	Panel B: add market-level controls			
	(1)	(2)	(3)	(4)
Log(Employment HHI)	0.002	0.005***	0.002	0.001
	[0.001]	[0.001]	[0.002]	[0.002]
Log(Labor Productivity)	0.268***	0.269***	0.272***	0.094***
	[0.004]	[0.004]	[0.004]	[0.005]
Missing Labor Productivity	3.328***	3.332***	3.362***	1.101***
	[0.050]	[0.050]	[0.050]	[0.064]
Fraction of Missing Estab Labor Productivity	-0.046***	-0.046***	-0.048***	0.071***
	[0.006]	[0.006]	[0.007]	[0.006]
Log(Total Employment, D&B)	-0.011**	-0.023***	0.005	0.008
	[0.006]	[0.006]	[0.009]	[0.009]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.349	0.349	0.350	0.370

	Panel C: add sales-based HHI			
	(1)	(2)	(3)	(4)
Log(Employment HHI)	0.001	0.004***	0.001	0.000
	[0.001]	[0.001]	[0.002]	[0.002]
Log(Sale HHI)	0.021***	0.021***	0.021***	0.011***
	[0.001]	[0.001]	[0.001]	[0.001]
Sales HHI Missing	0.035	0.046	0.048	0.067**
	[0.031]	[0.031]	[0.031]	[0.029]
Log(Labor Productivity)	0.253***	0.254***	0.256***	0.088***
	[0.004]	[0.004]	[0.004]	[0.005]
Missing Labor Productivity	3.128***	3.123***	3.148***	0.971***
	[0.057]	[0.058]	[0.058]	[0.067]
Fraction of Missing Estab Labor Productivity	-0.086***	-0.086***	-0.087***	0.073***
	[0.006]	[0.006]	[0.006]	[0.006]
Log(Total Employment, D&B)	-0.010*	-0.022***	0.004	0.007
	[0.006]	[0.006]	[0.009]	[0.009]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.350	0.350	0.351	0.370

Table 3: **Effect of labor-market concentration on hourly wage using 2SLS**

The dependent variable in all estimations is worker's *Log(Hourly Wage)*. All estimations are weighted by the worker's personal weight. There are 7,223,866 individuals in the sample. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects		
	(1)	(2)	(3)
Log(Employment HHI)	-0.125***	-0.124***	-0.170***
	[0.034]	[0.034]	[0.040]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.337	0.338	0.366

	Panel B: add market-level controls		
	(1)	(2)	(3)
Log(Employment HHI)	-0.054**	-0.054**	-0.110***
	[0.022]	[0.022]	[0.024]
Log(Labor Productivity)	0.269***	0.269***	0.095***
	[0.004]	[0.004]	[0.005]
Missing Labor Productivity	3.332***	3.336***	1.111***
	[0.049]	[0.049]	[0.065]
Fraction of Missing Estab Labor Productivity	-0.045***	-0.046***	0.074***
	[0.007]	[0.007]	[0.006]
Log(Total Employment, D&B)	0.077**	0.066**	0.190***
	[0.035]	[0.034]	[0.042]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.349	0.349	0.368

	Panel C: add sales-based HHI		
	(1)	(2)	(3)
Log(Employment HHI)	-0.059***	-0.059***	-0.110***
	[0.022]	[0.022]	[0.024]
Log(Sale HHI)	0.021***	0.021***	0.011***
	[0.001]	[0.001]	[0.001]
Sales HHI Missing	0.035	0.044	0.069**
	[0.030]	[0.030]	[0.030]
Log(Labor Productivity)	0.254***	0.254***	0.088***
	[0.004]	[0.004]	[0.005]
Missing Labor Productivity	3.131***	3.128***	0.977***
	[0.057]	[0.057]	[0.068]
Fraction of Missing Estab Labor Productivity	-0.085***	-0.086***	0.075***
	[0.006]	[0.006]	[0.006]
Log(Total Employment, D&B)	0.084**	0.074**	0.189***
	[0.035]	[0.034]	[0.042]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.349	0.350	0.369

Table 4: **Effect of labor-market concentration on employer-sponsored health insurance coverage using 2SLS**

The dependent variable in all the estimations is a dummy variable indicating whether an individual has health insurance through a current or former employer or union. All the estimations are weighted by the personal weight. There are 3,536,391 individuals in the sample. Standard errors in brackets allow clustered errors at the CZ-occupation level. The full estimation results are available in Table A.4.

	Panel A: only fixed effects		
	(1)	(2)	(3)
Log(Employment HHI)	0.034	0.032	-0.210
	[0.105]	[0.099]	[0.217]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.180	0.180	0.195
	Panel B: add market-level controls		
	(1)	(2)	(3)
Log(Employment HHI)	0.009	0.008	-0.046
	[0.034]	[0.034]	[0.034]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.190	0.190	0.205
	Panel C: add sales-based HHI		
	(1)	(2)	(3)
Log(Employment HHI)	0.006	0.005	-0.046
	[0.033]	[0.034]	[0.034]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.191	0.191	0.205

Table 5: **Effect of labor-market concentration on workers' education using 2SLS**

The dependent variable in all estimations is a dummy variable indicating whether a worker has a bachelor degree. All the estimations are weighted by the personal weight. There are 7,163,583 individuals in the sample. Standard errors in brackets allow clustered errors at the CZ-occupation level. The full estimation results are available in Table A.7.

	Panel A: only fixed effects		
	(1)	(2)	(3)
Log(Employment HHI)	-0.049***	-0.048***	-0.052***
	[0.017]	[0.017]	[0.019]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.355	0.356	0.369
	Panel B: add market-level controls		
	(1)	(2)	(3)
Log(Employment HHI)	-0.029**	-0.030**	-0.034***
	[0.012]	[0.012]	[0.012]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.357	0.357	0.370
	Panel C: add sales-based HHI		
	(1)	(2)	(3)
Log(Employment HHI)	-0.031***	-0.032***	-0.034***
	[0.012]	[0.012]	[0.012]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.358	0.358	0.370

Table 6: **Controlling for human capital characteristics using 2SLS**

The dependent variables in columns (1)-(3) are *Log(Hourly Wage)*, a dummy variable indicating whether an individual has health insurance through a current or former employer or union, and a dummy variable indicating whether a worker has a bachelor degree, respectively. All estimations are weighted by the worker's personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	(1)	(2)	(3)
Log(Employment HHI)	-0.068***	-0.050	-0.027**
	[0.020]	[0.034]	[0.012]
Log(Sale HHI)	0.008***	0.004***	0.004***
	[0.001]	[0.000]	[0.000]
Sales HHI Missing	0.067**	-0.001	-0.015
	[0.027]	[0.021]	[0.034]
Log(Labor Productivity)	0.063***	0.018***	0.032***
	[0.004]	[0.003]	[0.003]
Missing Labor Productivity	0.677***	0.204***	0.384***
	[0.055]	[0.043]	[0.050]
Fraction of Missing Estab Labor Productivity	0.064***	0.040***	0.006**
	[0.005]	[0.003]	[0.003]
Log(Total Employment, D&B)	0.123***	0.106	0.049**
	[0.035]	[0.076]	[0.020]
Age	0.087***	-0.008***	0.012***
	[0.000]	[0.000]	[0.000]
Age^2	-0.001***	0.000***	-0.000***
	[0.000]	[0.000]	[0.000]
Male	0.146***	-0.020***	0.040***
	[0.002]	[0.001]	[0.001]
Black	-0.107***	-0.054***	-0.078***
	[0.002]	[0.002]	[0.001]
Other Race	-0.066***	-0.027***	0.009***
	[0.002]	[0.002]	[0.001]
Married	0.109***	0.096***	0.019***
	[0.001]	[0.001]	[0.001]
Hispanic	-0.062***	-0.096***	-0.133***
	[0.002]	[0.002]	[0.003]
US Born	0.089***	0.111***	-0.040***
	[0.002]	[0.002]	[0.002]
US Born Missing	0.087***	0.125***	-0.037***
	[0.005]	[0.004]	[0.004]
Full Time Job	0.224***	0.121***	0.028***
	[0.003]	[0.002]	[0.001]
Bachelor's Degree	0.235***	0.050***	
	[0.003]	[0.001]	
Bachelor's Degree Missing	0.120***	-0.027***	
	[0.005]	[0.004]	
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.475	0.250	0.380
N	7,223,866	3,536,391	7,163,583

Table 7: **Heterogeneous Effects of Labor Market Concentration using IV**

This table reports the heterogeneous effects of labor market concentration on labor compensation using 2SLS estimations. We use two instrumental variables: (1) the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in a year and (2) the interaction between the first instrument and *Log(Sale HHI)* or *Unionization Rate* or *Offshorability*. The dependent variables in Panels A and B are the natural logarithm of real hourly wage and a dummy variable indicating whether an individual has health insurance through a current or former employer or union, respectively. *Unionization Rate* is the 5-year average unionization rate in a major occupation group-state cell centered around a year in CPS. Occupation represents the major group in CPS. *Offshorability* measures the extent to which the tasks performed by occupations are offshorable and the data is from David Dorn's webpage. In column (1) in both panels, we drop observations in which *Sales HHI* is missing. The control variables are the same as the ones in column (4), Panel D of Table 3. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: Log(Hourly Wage)		
	(1)	(2)	(3)
Log(Employment HHI)	-0.159***	-0.113***	-0.105***
	[0.024]	[0.023]	[0.026]
Log(Employment HHI)*Log(Sale HHI)	-0.020***		
	[0.003]		
Log(Sale HHI)	-0.095***	0.011***	0.011***
	[0.016]	[0.001]	[0.001]
Log(Employment HHI)*Unionization Rate		0.059	
		[0.098]	
Unionization Rate		0.316	
		[0.522]	
Log(Employment HHI)*Offshorability			-0.009
			[0.009]
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.367	0.369	0.369
N	7,216,453	7,223,866	7,223,273
	Panel B: Employer-sponsored Health Insurance		
	(1)	(2)	(3)
Log(Employment HHI)	-0.055	-0.073*	-0.049
	[0.034]	[0.038]	[0.037]
Log(Employment HHI)*Log(Sale HHI)	-0.005***		
	[0.001]		
Log(Sale HHI)	-0.020***	0.005***	0.005***
	[0.007]	[0.000]	[0.000]
Log(Employment HHI)*Unionization Rate		0.375**	
		[0.177]	
Unionization Rate		2.009**	
		[0.945]	
Log(Employment HHI)*Offshorability			0.017
			[0.022]
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.205	0.205	0.205
N	3,533,827	3,536,391	3,536,166

Appendix A Appendix: Qiu & Sojourner (October 18, 2019)

Table A.1: **First stage regressions for Table 3**

The dependent variable in all the estimations is *Log(Employment HHI)*. For each CZ-occupation-year cell, IV is the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in a year. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects		
	(1)	(2)	(3)
IV	0.070***	0.070***	0.068***
	[0.006]	[0.006]	[0.006]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.938	0.946	0.947
N	7,223,866	7,223,866	7,223,866
Kleibergen-Paap F-stat	133.27	122.94	111.48

	Panel B: add market-level controls		
	(1)	(2)	(3)
IV	0.101***	0.100***	0.106***
	[0.006]	[0.007]	[0.007]
Log(Labor Productivity)	0.007***	0.006***	0.010***
	[0.001]	[0.001]	[0.002]
Missing Labor Productivity	0.071***	0.072***	0.109***
	[0.016]	[0.015]	[0.030]
Fraction of Missing Estab Labor Productivity	0.015***	0.012***	0.022***
	[0.002]	[0.002]	[0.005]
Log(Total Employment, D&B)	1.592***	1.522***	1.757***
	[0.073]	[0.073]	[0.072]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.947	0.953	0.956
N	7,223,866	7,223,866	7,223,866
Kleibergen-Paap F-stat	248.32	230.79	254.30

	Panel C: add sales-based HHI		
	(1)	(2)	(3)
IV	0.101***	0.100***	0.106***
	[0.006]	[0.007]	[0.007]
Log(Sale HHI)	0.002***	0.002***	0.003***
	[0.001]	[0.001]	[0.001]
Sales HHI Missing	-0.009	-0.032	0.014
	[0.042]	[0.041]	[0.043]
Log(Labor Productivity)	0.005***	0.005***	0.008***
	[0.001]	[0.001]	[0.002]
Missing Labor Productivity	0.061	0.085**	0.077
	[0.044]	[0.043]	[0.053]
Fraction of Missing Estab Labor Productivity	0.011***	0.009***	0.022***
	[0.002]	[0.002]	[0.005]
Log(Total Employment, D&B)	1.592***	1.522***	1.756***
	[0.073]	[0.073]	[0.071]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.947	0.953	0.956
N	7,223,866	7,223,866	7,223,866
Kleibergen-Paap F-stat	248.07	230.54	254.08

Table A.2: **Control for national demand shock in Table 3**

The dependent variable in all estimations is worker's *Log(Hourly Wage)*. We include the natural logarithm of total sales in an occupation in a year to control for the demand shock for an occupation at the national level. All estimations are weighted by the worker's personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects		
	(1)	(2)	(3)
Log(Employment HHI)	-0.128***	-0.126***	-0.183***
	[0.035]	[0.035]	[0.043]
Log(Sale, OCC-Year)	-0.011	-0.011	-0.047***
	[0.008]	[0.008]	[0.010]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.337	0.338	0.366
N	7,223,866	7,223,866	7,223,866

	Panel B: add market-level controls		
	(1)	(2)	(3)
Log(Employment HHI)	-0.063***	-0.063***	-0.127***
	[0.023]	[0.023]	[0.027]
Log(Labor Productivity)	0.269***	0.270***	0.095***
	[0.004]	[0.004]	[0.005]
Missing Labor Productivity	3.340***	3.344***	1.111***
	[0.049]	[0.049]	[0.065]
Fraction of Missing Estab Labor Productivity	-0.045***	-0.046***	0.074***
	[0.007]	[0.007]	[0.006]
Log(Total Employment, D&B)	0.115***	0.105**	0.269***
	[0.042]	[0.041]	[0.056]
Log(Sale, OCC-Year)	-0.080***	-0.078***	-0.151***
	[0.017]	[0.016]	[0.029]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.349	0.349	0.368
N	7,223,866	7,223,866	7,223,866

	Panel C: add sales-based HHI		
	(1)	(2)	(3)
Log(Employment HHI)	-0.069***	-0.069***	-0.127***
	[0.023]	[0.023]	[0.027]
Log(Sale HHI)	0.021***	0.021***	0.011***
	[0.001]	[0.001]	[0.001]
Sales HHI Missing	0.036	0.046	0.070**
	[0.030]	[0.030]	[0.030]
Log(Labor Productivity)	0.254***	0.255***	0.088***
	[0.004]	[0.004]	[0.005]
Missing Labor Productivity	3.138***	3.134***	0.976***
	[0.057]	[0.057]	[0.068]
Fraction of Missing Estab Labor Productivity	-0.086***	-0.086***	0.076***
	[0.006]	[0.006]	[0.006]
Log(Total Employment, D&B)	0.128***	0.118***	0.268***
	[0.042]	[0.041]	[0.057]
Log(Sale, OCC-Year)	-0.091***	-0.089***	-0.151***
	[0.017]	[0.016]	[0.029]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.349	0.349	0.368
N	7,223,866	7,223,866	7,223,866

Table A.3: **Effect of labor-market concentration on employer-sponsored health insurance coverage using OLS**

The dependent variable in all estimations is a dummy variable indicating whether an individual has health insurance through a current or former employer or union. All estimations are weighted by the worker's personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

Panel A: only fixed effects

	(1)	(2)	(3)	(4)
Log(Employment HHI)	0.000	-0.000	0.001	0.002
	[0.001]	[0.001]	[0.001]	[0.001]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.180	0.180	0.181	0.205
N	3,536,391	3,536,391	3,536,391	3,536,391

Panel B: add market-level controls

	(1)	(2)	(3)	(4)
Log(Employment HHI)	-0.001	-0.002	0.003*	0.004**
	[0.001]	[0.002]	[0.002]	[0.002]
Log(Labor Productivity)	0.131***	0.131***	0.134***	0.031***
	[0.002]	[0.002]	[0.002]	[0.004]
Missing Labor Productivity	1.519***	1.520***	1.552***	0.347***
	[0.024]	[0.024]	[0.025]	[0.043]
Fraction of Missing Estab Labor Productivity	0.088***	0.088***	0.086***	0.045***
	[0.003]	[0.003]	[0.003]	[0.004]
Log(Total Employment, D&B)	0.002	-0.001	-0.013	-0.015*
	[0.006]	[0.006]	[0.009]	[0.009]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.190	0.190	0.190	0.205
N	3,536,391	3,536,391	3,536,391	3,536,391

Panel C: add sales-based HHI

	(1)	(2)	(3)	(4)
Log(Employment HHI)	-0.002	-0.002	0.003	0.003*
	[0.001]	[0.002]	[0.002]	[0.002]
Log(Sale HHI)	0.011***	0.011***	0.011***	0.005***
	[0.000]	[0.000]	[0.000]	[0.000]
Sales HHI Missing	-0.007	-0.006	-0.007	-0.002
	[0.019]	[0.020]	[0.020]	[0.020]
Log(Labor Productivity)	0.122***	0.122***	0.125***	0.027***
	[0.002]	[0.002]	[0.002]	[0.004]
Missing Labor Productivity	1.423***	1.422***	1.456***	0.310***
	[0.029]	[0.029]	[0.029]	[0.045]
Fraction of Missing Estab Labor Productivity	0.066***	0.066***	0.065***	0.046***
	[0.003]	[0.003]	[0.003]	[0.003]
Log(Total Employment, D&B)	0.003	-0.000	-0.017*	-0.017**
	[0.006]	[0.006]	[0.009]	[0.009]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.191	0.191	0.191	0.205
N	3,536,391	3,536,391	3,536,391	3,536,391

Table A.4: **Effect of labor-market concentration on employer-sponsored health insurance coverage using 2SLS—Full Estimations**

The dependent variable in all the estimations is a dummy variable indicating whether an individual has health insurance through a current or former employer or union. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects		
	(1)	(2)	(3)
Log(Employment HHI)	0.034	0.032	-0.210
	[0.105]	[0.099]	[0.217]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.180	0.180	0.195
N	3,536,391	3,536,391	3,536,391

	Panel B: add market-level controls		
	(1)	(2)	(3)
Log(Employment HHI)	0.009	0.008	-0.046
	[0.034]	[0.034]	[0.034]
Log(Labor Productivity)	0.131***	0.131***	0.031***
	[0.002]	[0.002]	[0.004]
Missing Labor Productivity	1.518***	1.519***	0.354***
	[0.024]	[0.024]	[0.044]
Fraction of Missing Estab Labor Productivity	0.088***	0.088***	0.045***
	[0.003]	[0.003]	[0.004]
Log(Total Employment, D&B)	-0.020	-0.021	0.098
	[0.073]	[0.070]	[0.077]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.190	0.190	0.205
N	3,536,391	3,536,391	3,536,391

	Panel C: add sales-based HHI		
	(1)	(2)	(3)
Log(Employment HHI)	0.006	0.005	-0.046
	[0.033]	[0.034]	[0.034]
Log(Sale HHI)	0.011***	0.011***	0.005***
	[0.000]	[0.000]	[0.000]
Sales HHI Missing	-0.007	-0.006	-0.003
	[0.019]	[0.020]	[0.020]
Log(Labor Productivity)	0.122***	0.122***	0.028***
	[0.002]	[0.002]	[0.004]
Missing Labor Productivity	1.422***	1.422***	0.318***
	[0.029]	[0.029]	[0.046]
Fraction of Missing Estab Labor Productivity	0.066***	0.066***	0.046***
	[0.003]	[0.003]	[0.004]
Log(Total Employment, D&B)	-0.015	-0.016	0.098
	[0.073]	[0.070]	[0.077]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.191	0.191	0.205
N	3,536,391	3,536,391	3,536,391

Table A.5: **First stage regressions for Table 4**

The dependent variable in all the estimations is *Log(Employment HHI)*. For each CZ-occupation-year cell, IV is the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in a year. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

Panel A: only fixed effects

	(1)	(2)	(3)
IV	0.014**	0.015**	0.010
	[0.007]	[0.007]	[0.007]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.968	0.972	0.972
N	3,536,391	3,536,391	3,536,391
Kleibergen-Paap F-stat	4.61	4.92	2.07

Panel B: add market-level controls

	(1)	(2)	(3)
IV	0.047***	0.046***	0.048***
	[0.007]	[0.007]	[0.007]
Log(Labor Productivity)	0.011***	0.009***	0.012***
	[0.001]	[0.001]	[0.002]
Missing Labor Productivity	0.128***	0.109***	0.141***
	[0.015]	[0.013]	[0.027]
Fraction of Missing Estab Labor Productivity	0.002	0.003**	0.002
	[0.002]	[0.001]	[0.003]
Log(Total Employment, D&B)	2.176***	2.077***	2.254***
	[0.135]	[0.138]	[0.131]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.976	0.978	0.980
N	3,536,391	3,536,391	3,536,391
Kleibergen-Paap F-stat	47.64	46.09	51.02

Panel C: add sales-based HHI

	(1)	(2)	(3)
IV	0.047***	0.046***	0.048***
	[0.007]	[0.007]	[0.007]
Log(Sale HHI)	0.001***	0.001**	0.001***
	[0.000]	[0.000]	[0.000]
Sales HHI Missing	-0.031	-0.008	0.001
	[0.023]	[0.021]	[0.022]
Log(Labor Productivity)	0.010***	0.009***	0.011***
	[0.001]	[0.001]	[0.002]
Missing Labor Productivity	0.143***	0.109***	0.130***
	[0.026]	[0.025]	[0.034]
Fraction of Missing Estab Labor Productivity	-0.001	0.002	0.002
	[0.002]	[0.002]	[0.003]
Log(Total Employment, D&B)	2.176***	2.077***	2.253***
	[0.135]	[0.138]	[0.131]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.976	0.978	0.980
N	3,536,391	3,536,391	3,536,391
Kleibergen-Paap F-stat	47.59	46.06	50.99

Table A.6: **Effect of labor-market concentration on workers' education using OLS**

The dependent variable in all estimations is a dummy variable indicating whether a worker has a bachelor degree. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects			
	(1)	(2)	(3)	(4)
Log(Employment HHI)	0.001***	0.001**	0.001*	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.357	0.357	0.357	0.370
N	7,163,583	7,163,583	7,163,583	7,163,583

	Panel B: add market-level controls			
	(1)	(2)	(3)	(4)
Log(Employment HHI)	0.001**	0.001*	0.001*	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
Log(Labor Productivity)	0.033***	0.033***	0.034***	0.035***
	[0.002]	[0.002]	[0.002]	[0.003]
Missing Labor Productivity	0.430***	0.433***	0.439***	0.415***
	[0.020]	[0.020]	[0.020]	[0.038]
Fraction of Missing Estab Labor Productivity	-0.021***	-0.021***	-0.022***	0.001
	[0.003]	[0.003]	[0.003]	[0.003]
Log(Total Employment, D&B)	-0.002	-0.002	-0.004	-0.003
	[0.003]	[0.003]	[0.004]	[0.004]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.357	0.358	0.358	0.370
N	7,163,583	7,163,583	7,163,583	7,163,583

	Panel C: add sales-based HHI			
	(1)	(2)	(3)	(4)
Log(Employment HHI)	0.001*	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
Log(Sale HHI)	0.009***	0.009***	0.009***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]
Sales HHI Missing	-0.039	-0.040	-0.039	-0.020
	[0.037]	[0.038]	[0.038]	[0.035]
Log(Labor Productivity)	0.027***	0.027***	0.027***	0.033***
	[0.001]	[0.001]	[0.001]	[0.003]
Missing Labor Productivity	0.393***	0.397***	0.400***	0.409***
	[0.040]	[0.041]	[0.042]	[0.051]
Fraction of Missing Estab Labor Productivity	-0.038***	-0.038***	-0.038***	0.002
	[0.003]	[0.003]	[0.003]	[0.003]
Log(Total Employment, D&B)	-0.001	-0.001	-0.004	-0.003
	[0.003]	[0.003]	[0.004]	[0.004]
CZ × OCC FE	Y	Y	Y	Y
Year FE	Y			
CZ × Year FE		Y	Y	Y
OCC × Year FE			Y	Y
Ind × Year FE				Y
Labor Market Trends	Y	Y	Y	Y
Adj. R^2	0.358	0.358	0.358	0.370
N	7,163,583	7,163,583	7,163,583	7,163,583

Table A.7: **Effect of labor-market concentration on workers' education using 2SLS—Full Estimations**

The dependent variable in all estimations is a dummy variable indicating whether a worker has a bachelor degree. All the estimations are weighted by the personal weight.Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects		
	(1)	(2)	(3)
Log(Employment HHI)	-0.049***	-0.048***	-0.052***
	[0.017]	[0.017]	[0.019]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.355	0.356	0.369
N	7,163,583	7,163,583	7,163,583

	Panel B: add market-level controls		
	(1)	(2)	(3)
Log(Employment HHI)	-0.029**	-0.030**	-0.034***
	[0.012]	[0.012]	[0.012]
Log(Labor Productivity)	0.033***	0.033***	0.036***
	[0.002]	[0.002]	[0.003]
Missing Labor Productivity	0.432***	0.435***	0.418***
	[0.020]	[0.020]	[0.038]
Fraction of Missing Estab Labor Productivity	-0.021***	-0.021***	0.002
	[0.003]	[0.003]	[0.003]
Log(Total Employment, D&B)	0.047**	0.044**	0.059***
	[0.019]	[0.018]	[0.021]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.357	0.357	0.370
N	7,163,583	7,163,583	7,163,583

	Panel C: add sales-based HHI		
	(1)	(2)	(3)
Log(Employment HHI)	-0.031***	-0.032***	-0.034***
	[0.012]	[0.012]	[0.012]
Log(Sale HHI)	0.009***	0.009***	0.004***
	[0.000]	[0.000]	[0.000]
Sales HHI Missing	-0.040	-0.041	-0.020
	[0.036]	[0.037]	[0.034]
Log(Labor Productivity)	0.027***	0.027***	0.034***
	[0.001]	[0.001]	[0.003]
Missing Labor Productivity	0.395***	0.399***	0.411***
	[0.040]	[0.041]	[0.050]
Fraction of Missing Estab Labor Productivity	-0.037***	-0.038***	0.002
	[0.003]	[0.003]	[0.003]
Log(Total Employment, D&B)	0.050***	0.048***	0.058***
	[0.019]	[0.018]	[0.021]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.358	0.358	0.370
N	7,163,583	7,163,583	7,163,583

Table A.8: **First stage regressions for Table 5**

The dependent variable in all the estimations is *Log(Employment HHI)*. For each CZ-occupation-year cell, IV is the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in a year. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: only fixed effects		
	(1)	(2)	(3)
IV	0.070***	0.070***	0.068***
	[0.006]	[0.006]	[0.006]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.938	0.946	0.948
N	7,163,583	7,163,583	7,163,583
Kleibergen-Paap F-stat	134.06	123.70	112.15

	Panel B: add market-level controls		
	(1)	(2)	(3)
IV	0.100***	0.100***	0.106***
	[0.006]	[0.007]	[0.007]
Log(Labor Productivity)	0.007***	0.006***	0.010***
	[0.001]	[0.001]	[0.002]
Missing Labor Productivity	0.070***	0.071***	0.111***
	[0.016]	[0.015]	[0.030]
Fraction of Missing Estab Labor Productivity	0.015***	0.012***	0.022***
	[0.002]	[0.002]	[0.005]
Log(Total Employment, D&B)	1.590***	1.519***	1.754***
	[0.072]	[0.072]	[0.071]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.947	0.953	0.956
N	7,163,583	7,163,583	7,163,583
Kleibergen-Paap F-stat	249.72	231.84	255.05

	Panel C: add sales-based HHI		
	(1)	(2)	(3)
IV	0.100***	0.100***	0.106***
	[0.006]	[0.007]	[0.007]
Log(Sale HHI)	0.002***	0.002***	0.003***
	[0.001]	[0.001]	[0.001]
Sales HHI Missing	-0.008	-0.031	0.015
	[0.042]	[0.041]	[0.043]
Log(Labor Productivity)	0.005***	0.005***	0.008***
	[0.001]	[0.001]	[0.002]
Missing Labor Productivity	0.060	0.084*	0.078
	[0.045]	[0.043]	[0.053]
Fraction of Missing Estab Labor Productivity	0.011***	0.009***	0.022***
	[0.002]	[0.002]	[0.005]
Log(Total Employment, D&B)	1.590***	1.519***	1.753***
	[0.072]	[0.072]	[0.071]
CZ × OCC FE	Y	Y	Y
Year FE	Y		
CZ × Year FE		Y	Y
Ind × Year FE			Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.947	0.953	0.956
N	7,163,583	7,163,583	7,163,583
Kleibergen-Paap F-stat	249.47	231.60	254.82

Table A.9: **Heterogeneous Effects of Labor Market Concentration using OLS**

This table reports the heterogeneous effects of labor-market concentration on labor compensation using OLS estimations. The dependent variables in Panels A and B are the natural logarithm of real hourly wage and an indicator variable for whether an individual has employment-based health insurance, respectively. *Unionization Rate* is the 5-year average unionization rate in an occupation major group by state cell centered around a year in CPS. *Offshorability* measures the extent to which the tasks performed by occupations are offshorable and is from David Dorn's webpage. In column (1) in both panels, we drop observations in which *Sales HHI* is missing. The control variables are the same as the ones in column (4), Panel D of Table 3. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: Log(Hourly Wage)		
	(1)	(2)	(3)
Log(Employment HHI)	-0.001	0.002	0.000
	[0.002]	[0.002]	[0.002]
Log(Employment HHI)*Log(Sale HHI)	-0.000		
	[0.000]		
Log(Employment HHI)*Unionization Rate		-0.021	
		[0.014]	
Unionization Rate		-0.170**	
		[0.079]	
Log(Employment HHI)*Offshorability			0.000
			[0.001]
Log(Sale HHI)	0.010***	0.011***	0.011***
	[0.003]	[0.001]	[0.001]
Log(Labor Productivity)	0.088***	0.088***	0.088***
	[0.005]	[0.005]	[0.005]
Missing Labor Productivity	0.975***	0.972***	0.971***
	[0.068]	[0.067]	[0.067]
Fraction of Missing Estab Labor Productivity	0.073***	0.073***	0.073***
	[0.006]	[0.006]	[0.006]
Log(Total Employment, D&B)	0.008	0.007	0.007
	[0.009]	[0.009]	[0.009]
Sales HHI Missing		0.066**	0.067**
		[0.029]	[0.029]
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
OCC × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.370	0.370	0.370
N	7,216,453	7,223,866	7,223,273

	Panel B: Employer-sponsored Health Insurance		
	(1)	(2)	(3)
Log(Employment HHI)	-0.002	0.003	0.003*
	[0.002]	[0.002]	[0.002]
Log(Employment HHI)*Log(Sale HHI)	-0.002***		
	[0.000]		
Log(Employment HHI)*Unionization Rate		0.007	
		[0.015]	
Unionization Rate		0.040	
		[0.087]	
Log(Employment HHI)*Offshorability			-0.000
			[0.001]
Log(Sale HHI)	-0.004***	0.005***	0.005***
	[0.001]	[0.000]	[0.000]
Log(Labor Productivity)	0.028***	0.027***	0.027***
	[0.004]	[0.004]	[0.004]
Missing Labor Productivity	0.314***	0.309***	0.310***
	[0.046]	[0.045]	[0.045]
Fraction of Missing Estab Labor Productivity	0.045***	0.046***	0.046***
	[0.003]	[0.003]	[0.003]
Log(Total Employment, D&B)	-0.011	-0.017*	-0.017*
	[0.009]	[0.009]	[0.009]
Sales HHI Missing		-0.002	-0.002
		[0.020]	[0.020]
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
OCC × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.205	0.205	0.205
N	3,533,827	3,536,391	3,536,166

Table A.10: **Heterogeneous Effects of Labor Market Concentration using IV—Full Estimations**

This table reports the heterogeneous effects of labor market concentration on labor compensation using 2SLS estimations. We use two instrumental variables: (1) the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in a year and (2) the interaction between the first instrument and *Log(Sale HHI)* or *Unionization Rate* or *Offshorability*. The dependent variables in Panels A and B are the natural logarithm of real hourly wage and a dummy variable indicating whether an individual has health insurance through a current or former employer or union, respectively. *Unionization Rate* is the 5-year average unionization rate in a major occupation group-state cell centered around a year in CPS. Occupation represents the major group in CPS. *Offshorability* measures the extent to which the tasks performed by occupations are offshorable and the data is from David Dorn's webpage. In column (1) in both panels, we drop observations in which *Sales HHI* is missing. The control variables are the same as the ones in column (4), Panel D of Table 3. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: Log(Hourly Wage)		
	(1)	(2)	(3)
Log(Employment HHI)	-0.159***	-0.113***	-0.105***
	[0.024]	[0.023]	[0.026]
Log(Employment HHI)*Log(Sale HHI)	-0.020***		
	[0.003]		
Log(Sale HHI)	-0.095***	0.011***	0.011***
	[0.016]	[0.001]	[0.001]
Log(Employment HHI)*Unionization Rate		0.059	
		[0.098]	
Unionization Rate		0.316	
		[0.522]	
Log(Employment HHI)*Offshorability			-0.009
			[0.009]
Log(Labor Productivity)	0.096***	0.088***	0.088***
	[0.006]	[0.005]	[0.005]
Missing Labor Productivity	1.074***	0.976***	0.976***
	[0.072]	[0.068]	[0.068]
Fraction of Missing Estab Labor Productivity	0.069***	0.075***	0.075***
	[0.006]	[0.006]	[0.006]
Log(Total Employment, D&B)	0.205***	0.186***	0.184***
	[0.042]	[0.044]	[0.044]
Sales HHI Missing		0.070**	0.069**
		[0.030]	[0.030]
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.367	0.369	0.369
N	7,216,453	7,223,866	7,223,273
	Panel B: Employer-sponsored Health Insurance		
	(1)	(2)	(3)
Log(Employment HHI)	-0.055	-0.073*	-0.049
	[0.034]	[0.038]	[0.037]
Log(Employment HHI)*Log(Sale HHI)	-0.005***		
	[0.001]		
Log(Sale HHI)	-0.020***	0.005***	0.005***
	[0.007]	[0.000]	[0.000]
Log(Employment HHI)*Unionization Rate		0.375**	
		[0.177]	
Unionization Rate		2.009**	
		[0.945]	
Log(Employment HHI)*Offshorability			0.017
			[0.022]
Log(Labor Productivity)	0.029***	0.028***	0.028***
	[0.004]	[0.004]	[0.004]
Missing Labor Productivity	0.338***	0.315***	0.318***
	[0.047]	[0.046]	[0.046]
Fraction of Missing Estab Labor Productivity	0.045***	0.045***	0.046***
	[0.003]	[0.004]	[0.004]
Log(Total Employment, D&B)	0.097	0.092	0.087
	[0.077]	[0.077]	[0.071]
Sales HHI Missing		-0.001	-0.004
		[0.020]	[0.020]
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.205	0.205	0.205
N	3,533,827	3,536,391	3,536,166

Table A.11: **First stage regressions for Table 7**

The dependent variable in columns (1), (3), and (5) is *Log(Employment HHI)*. The dependent variables in columns (2), (4), and (6) are *Log(Employment HHI)×Log(Sales HHI)*, *Log(Employment HHI)×Unionization Rate*, and *Log(Employment HHI)×Offshorability*, respectively. For each CZ-occupation-year cell, IV is the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in a year. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	Panel A: Log(Hourly Wage)					
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.111***	0.791***	0.118***	-0.014***	0.105***	0.058***
	[0.007]	[0.080]	[0.008]	[0.001]	[0.007]	[0.009]
IV*Log(Sale HHI)	0.002**	0.435***				
	[0.001]	[0.033]				
IV*Unionization Rate			-0.203**	0.319***		
			[0.095]	[0.021]		
Unionization Rate			-1.770**	-2.588***		
			[0.809]	[0.177]		
IV*Offshorability					0.031***	0.213***
					[0.006]	[0.014]
Log(Sale HHI)	0.022**	-1.552***	0.003***	0.000**	0.003***	0.001
	[0.010]	[0.285]	[0.001]	[0.000]	[0.001]	[0.001]
Log(Labor Productivity)	0.008***	0.329***	0.008***	0.001***	0.008***	0.001
	[0.003]	[0.041]	[0.003]	[0.000]	[0.002]	[0.003]
Missing Labor Productivity	0.075	4.493***	0.076	0.019	0.076	0.018
	[0.054]	[0.618]	[0.054]	[0.014]	[0.054]	[0.049]
Fraction of Missing Estab Labor Productivity	0.022***	-0.377***	0.022***	0.003***	0.022***	-0.022***
	[0.005]	[0.042]	[0.005]	[0.001]	[0.005]	[0.007]
Log(Total Employment, D&B)	1.757***	-3.488***	1.757***	0.153***	1.760***	0.447***
	[0.072]	[0.157]	[0.071]	[0.008]	[0.071]	[0.132]
Sales HHI Missing			0.014	-0.008	0.014	0.003
			[0.043]	[0.013]	[0.043]	[0.031]
CZ × OCC FE	Y	Y	Y	Y	Y	Y
CZ × Year FE	Y	Y	Y	Y	Y	Y
Ind × Year FE	Y	Y	Y	Y	Y	Y
Labor Market Trends	Y	Y	Y	Y	Y	Y
Adj. R^2	0.956	0.972	0.956	0.991	0.956	0.996
N	7,216,453	7,216,453	7,223,866	7,223,866	7,223,273	7,223,273
Kleibergen-Paap F-stat		125.88		109.86		109.88

	Panel B: Employer-sponsored Health Insurance					
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.050***	0.991***	0.041***	-0.006***	0.049***	0.013*
	[0.007]	[0.099]	[0.008]	[0.001]	[0.007]	[0.007]
IV*Log(Sale HHI)	0.001	0.455***				
	[0.001]	[0.041]				
IV*Unionization Rate			0.112	0.168***		
			[0.075]	[0.020]		
Unionization Rate			1.040	-3.866***		
			[0.634]	[0.176]		
IV*Offshorability					0.022***	0.068***
					[0.004]	[0.007]
Log(Sale HHI)	0.008	-1.348***	0.001***	0.000	0.001***	0.001
	[0.007]	[0.354]	[0.000]	[0.000]	[0.000]	[0.000]
Log(Labor Productivity)	0.011***	0.414***	0.011***	0.001**	0.011***	0.002
	[0.002]	[0.059]	[0.002]	[0.000]	[0.002]	[0.003]
Missing Labor Productivity	0.132***	5.521***	0.131***	0.018*	0.130***	0.018
	[0.034]	[0.846]	[0.034]	[0.010]	[0.034]	[0.044]
Fraction of Missing Estab Labor Productivity	0.002	-0.272***	0.002	0.002***	0.002	-0.018***
	[0.003]	[0.052]	[0.003]	[0.000]	[0.003]	[0.005]
Log(Total Employment, D&B)	2.254***	-4.303***	2.253***	0.176***	2.257***	0.992***
	[0.131]	[0.221]	[0.131]	[0.016]	[0.130]	[0.307]
Sales HHI Missing			0.001	-0.008	0.001	0.012
			[0.022]	[0.010]	[0.023]	[0.020]
CZ × OCC FE	Y	Y	Y	Y	Y	Y
CZ × Year FE	Y	Y	Y	Y	Y	Y
Ind × Year FE	Y	Y	Y	Y	Y	Y
Labor Market Trends	Y	Y	Y	Y	Y	Y
Adj. R^2	0.980	0.975	0.980	0.996	0.980	0.998
N	3,533,827	3,533,827	3,536,391	3,536,391	3,536,166	3,536,166
Kleibergen-Paap F-stat		25.56		25.91		25.85

Table A.12: **Controlling for human capital characteristics using OLS**

The dependent variables in columns (1)-(4) are *Log(Hourly Wage)*, a dummy variable indicating whether an individual has health insurance through a current or former employer or union, a dummy variable indicating whether a worker has a bachelor degree, and a dummy variable indicating whether an individual is employed in a year, respectively. All estimations are weighted by the worker's personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	(1)	(2)	(3)
Log(Employment HHI)	-0.000	0.003	0.001
	[0.002]	[0.002]	[0.001]
Log(Sale HHI)	0.007***	0.004***	0.003***
	[0.001]	[0.000]	[0.000]
Sales HHI Missing	0.066**	-0.000	-0.014
	[0.027]	[0.021]	[0.035]
Log(Labor Productivity)	0.063***	0.018***	0.032***
	[0.004]	[0.003]	[0.003]
Missing Labor Productivity	0.673***	0.196***	0.382***
	[0.055]	[0.043]	[0.050]
Fraction of Missing Estab Labor Productivity	0.062***	0.040***	0.005*
	[0.005]	[0.003]	[0.003]
Log(Total Employment, D&B)	0.009	-0.017*	-0.002
	[0.008]	[0.009]	[0.004]
Age	0.087***	-0.008***	0.012***
	[0.000]	[0.000]	[0.000]
Age^2	-0.001***	0.000***	-0.000***
	[0.000]	[0.000]	[0.000]
Male	0.146***	-0.020***	0.040***
	[0.002]	[0.001]	[0.001]
Black	-0.107***	-0.054***	-0.078***
	[0.002]	[0.002]	[0.001]
Other Race	-0.066***	-0.027***	0.009***
	[0.002]	[0.002]	[0.001]
Married	0.109***	0.096***	0.019***
	[0.001]	[0.001]	[0.001]
Hispanic	-0.062***	-0.096***	-0.133***
	[0.002]	[0.002]	[0.003]
US Born	0.089***	0.111***	-0.040***
	[0.002]	[0.002]	[0.002]
US Born Missing	0.087***	0.125***	-0.036***
	[0.005]	[0.004]	[0.004]
Full Time Job	0.224***	0.121***	0.028***
	[0.003]	[0.002]	[0.001]
Bachelor's Degree	0.235***	0.050***	
	[0.003]	[0.001]	
Bachelor's Degree Missing	0.119***	-0.028***	
	[0.005]	[0.004]	
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
OCC × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.475	0.250	0.380
N	7,223,866	3,536,391	7,163,583

Table A.13: **First stage regressions for Table 6**

The dependent variable in all the estimations is *Log(Employment HHI)*. For each CZ-occupation-year cell, IV is the average of the natural logarithm of one over the number of firms in the same occupation but in other CZs in a year. All the estimations are weighted by the personal weight. Standard errors in brackets allow clustered errors at the CZ-occupation level.

	(1)	(2)	(3)
IV	0.106***	0.048***	0.106***
	[0.007]	[0.007]	[0.007]
Log(Sale HHI)	0.003***	0.001***	0.003***
	[0.001]	[0.000]	[0.001]
Sales HHI Missing	0.014	0.001	0.015
	[0.043]	[0.022]	[0.043]
Log(Labor Productivity)	0.008***	0.011***	0.008***
	[0.002]	[0.002]	[0.002]
Missing Labor Productivity	0.076	0.130***	0.078
	[0.053]	[0.034]	[0.053]
Fraction of Missing Estab Labor Productivity	0.022***	0.002	0.022***
	[0.005]	[0.003]	[0.005]
Log(Total Employment, D&B)	1.756***	2.253***	1.753***
	[0.071]	[0.131]	[0.071]
Age	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]
Age^2	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Male	-0.000	0.000	-0.000
	[0.000]	[0.000]	[0.000]
Black	0.000	-0.001	-0.000
	[0.001]	[0.000]	[0.001]
Other Race	0.001	0.000	0.001
	[0.001]	[0.000]	[0.001]
Married	0.001**	0.001**	0.001**
	[0.000]	[0.000]	[0.000]
Hispanic	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]
US Born	-0.000	0.000	-0.000
	[0.000]	[0.000]	[0.000]
US Born Missing	0.001	0.002	0.001
	[0.002]	[0.002]	[0.002]
Full Time Job	-0.000	0.000	-0.000
	[0.000]	[0.000]	[0.000]
Bachelor's Degree	0.001*	0.000	
	[0.000]	[0.000]	
Bachelor's Degree Missing	-0.002	-0.001	
	[0.002]	[0.001]	
CZ × OCC FE	Y	Y	Y
CZ × Year FE	Y	Y	Y
Ind × Year FE	Y	Y	Y
Labor Market Trends	Y	Y	Y
Adj. R^2	0.956	0.980	0.956
N	7,223,866	3,536,391	7,163,583
Kleibergen-Paap F-stat	254.11	50.99	254.85