Strong Employers and Weak Employees

How Does Employer Concentration Affect Wages?

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ABSTRACT

We analyze the effect of local-level labor market concentration on wages. Using plant-level U.S. Census data during 1978–2016, we find that: (i) local-level employer concentration exhibits substantial cross-sectional variation; (ii) consistent with labor market monopsony power, there is a negative relation between local-level employer concentration and wages that strengthens with time; (iii) instrumenting concentration with merger activity shows that increased employer concentration decreases wages; (iv) the negative relation between employer concentration and wages increases when unionization rates are low; and (v) the link between productivity growth and wage growth is stronger when labor markets are less concentrated. Our results emphasize the role of local labor market monopsonies in influencing firm wage-setting.

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[Submitted January 2019; accepted March 2020]; doi:10.3368/jhr.monopsony.0119-10007R1
JEL Classification: E24, J51, J61, J62, and L13
ISSN 0022-166X E-ISSN 1548-8004

I. Introduction

A growing body of work showing rising levels of market concentration in the United States (see, for example, Barkai 2020; Grullon, Larkin, and Michaely 2019; Autor et al. 2017) has made it increasingly difficult to support the assumption of perfectly competitive labor markets as an adequate description of wage-setting processes. Rather than acting as price-takers faced with an infinitely elastic labor supply curve, a casual empiricism would suggest that firms enjoy at least some degree of wage-setting ability, often bargaining with workers over the surplus created by employment.[1]

One potentially important source of wage-setting ability stems from firms' market power within labor markets: wages may be set in imperfectly competitive markets, with a relatively small number of employers bargaining with workers, ultimately setting wages below perfectly competitive rates (see, for example, Manning 2003).[2] Much of the evidence on such market power within labor markets is either indirect or limited in nature.[3] Important examples include evidence on lawsuits against employer collusion using antipoaching agreements (U.S. Department of Justice Office of Public Affairs 2014; Whitney 2015), studies focused on particular occupations such as teaching or nursing (for example, Sullivan 1989; Staiger, Spetz, and Phibbs 2010; Ransom and Sims 2010), evidence on employee noncompete restrictions and franchisee nonpoaching clauses (Krueger and Ashenfelter 2022; Starr, Prescott, and Bishara 2019), as well as the large literature beginning with Card and Krueger (1994) showing that minimum wage increases are not followed by reductions in employment, consistent with non–perfectly competitive labor markets.[4]

We use microlevel data from the U.S. Census Bureau to analyze how market power stemming from employer concentration in local labor markets—that is, monopsony power—affects wage behavior in the U.S. manufacturing sector. Because the relevant market associated with job search is largely local (Manning and Petrongolo 2017)—

Conference on the Political Economy of Finance 2018 for very helpful comments. They thank Eric Kim, Honghao Wang, and Zhenzhi He for research assistance, as well as Bert Grider at the TRFSRDC and Nichole Szembrot at the NYFSRDC (Cornell) for helping with data and clearance requests. Bergman thanks the Pinhas Sapir Center for Development for financial support. All results have been reviewed by the U.S. Census Bureau to ensure that no confidential information is disclosed. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. Part of data used in this paper are drawn from the U.S. Census Bureau's confidential databases. The underlying Census databases can be accessed by submitting a research proposal directly to the U.S. Census Bureau (https://www.census.gov/programs-surveys/ces/data/restricted-use-data/apply-for-access.html). The authors are willing to assist (Hyunseob Kim, Hyunseob.Kim@chi.frb.org).

1. See Krueger (2018) for a survey of empirical evidence regarding worker bargaining power and applications to monetary policy.
2. Firms can benefit from bargaining power and wage-setting ability due to factors other than high concentration in labor markets. These include search costs, switching costs between jobs, firm-specific human capital, and heterogeneous firm characteristics, such as amenities or commuting times, that generate employer–employee match-specific capital (as in Flinn 2006).
3. Two exceptions are Azar, Marinescu, and Steinbaum (2022) and Rinz (2022).
4. Other studies show that the propensity of workers to leave their jobs after wage declines is smaller than would be expected in competitive markets, suggestive of employers' wage-setting ability (Dube, Lester, and Reich 2010, 2016).

labor mobility in the United States has declined significantly, and job switches often occur between positions in the same area (Moretti 2011; Molloy, Smith, and Wozniak 2014)—our analysis emphasizes the importance of measuring labor market concentration within relatively localized geographic areas.[5]

We combine two main sources of data from the U.S. Census Bureau over the sample period 1978–2016. First, to measure local-level labor market concentration, we use the Longitudinal Business Database (LBD) to construct the Herfindahl–Hirschman index (HHI) of firm employment at both the county-by-industry-by-year level as well as the commuting-zone-by-industry-by-year level. The HHI concentration measure is calculated at the local industry level (either county or commuting zone) under the plausible assumption that employees' specific human capital and mobility costs constrain their job searches toward firms within the same industry and geographical area. These HHI measures of employer concentration are then related to measures of average wages and productivity at the establishment level constructed from the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM). By focusing our analysis on manufacturing we are able to control for standard measures of labor productivity—an important correlate in any analysis of wage determination.[6]

We obtain six main results. First, local-level employer concentration exhibits significant cross-sectional variation. For example, during 1978–2016, the standard deviation of local-level employer HHI (defined over commuting zones and four-digit standard industry classification [SIC] codes) was 0.343, equal to approximately 70 percent of the mean local-level HHI of 0.481. Further, average levels of concentration have remained fairly stable during the sample period, with employment-weighted concentration levels increasing by no more than 3.2 percent. For example, the mean employment-weighted employer concentration HHI measure calculated at the four-digit SIC code and commuting zone was 0.569 during 1978–1987 and 0.587 during 2008–2016.

Our second result establishes our baseline finding: there is a negative relation between wages and the local-level HHI measures of employer concentration, with an elasticity of wages to HHI of approximately –0.01 over the full sample period. Employers operating in areas with more concentrated labor markets thus appear able to exploit monopsony power in order to reduce employee wages.

To mitigate concerns regarding correlations between the local-level HHI measure of concentration and other observable and unobservable differences across plants, industries, and local areas (see, for example, Boal and Ransom 1997), we show that our results continue to hold after controlling for a host of observables likely to affect wages. These include establishment-level labor productivity, local labor market size, and firm-by-year fixed effects. Identification is thus achieved using within firm–year variation, comparing multiple establishments belonging to the same firm but located in areas, or belonging to industries, with varying levels of labor market concentration. The findings are also robust to the use of industry-by-year fixed effects together with firm-by-year fixed effects.[7] This battery of controls removes any common cross-industry variation

5. See also Kim (2020) for a similar approach to defining local labor markets.

6. The census data do not allow us to calculate establishment-level productivity outside of manufacturing because establishment-level information on output and detailed price deflators for various inputs and output are not available for nonmanufacturing sectors.

7. We obtain identification of both industry-by-year as well as firm-by-year fixed effects because multi-establishment firms may operate establishments in more than one industry.

within firms, thereby alleviating cross-industry heterogeneity as an alternative channel that drives wage differences. In the preferred specification (with both firm-by-year and industry-by-year fixed effects), the results show that moving from one standard deviation below to one standard deviation above the mean level of local HHI is associated with a 2.9 percent decline in wages. We further show that our baseline results continue to hold in a subsample of firms that operate multiple plants in only one industry segment. Using this subsample in conjunction with firm-by-year fixed effects, we largely avoid the alternative explanation of cross-industry heterogeneity.

To further alleviate concerns regarding the endogeneity of local-level concentration, we employ an instrumental variable approach that uses merger and acquisition (M&A) activity to instrument for local-level employer concentration. In particular, we exploit variation in local-level employer concentration driven by M&A activity that reallocates the ownership of establishments between different firms. Using M&A activity to instrument for local-level employer concentration, our third result is that increased employer concentration leads to lower wages, with the elasticity of wages to local-level HHI rising to between –0.03 and –0.06. Based on the instrumental variable (IV) estimates (with commuting zones to define employer concentration), the results imply that moving from one standard deviation below to one standard deviation above the mean level of local HHI is associated with a decline in wages between 9.1 percent and 14.4 percent.

We continue by showing that the negative relation between employer concentration and wages monotonically increases in magnitude over the sample period. In the preferred specification, the elasticity in the initial decade of the sample (1978–1987) is a statistically insignificant –0.001, while in the last decade of the sample (2008–2016) the elasticity rises to –0.018. This increased sensitivity of wages to employer concentration is consistent with a secular decline in worker bargaining power over time, as would be predicted by the reduction in labor mobility in the United States (constraining the choice set of workers as they search for employment and negotiate over compensation) or by the drop in unionization rates within the United States beginning in the 1970s (Card 1992).

Our fourth finding concerns the impact of unionization on the relation between employer concentration and wages. We hypothesize that by improving employee bargaining power, unionization may diminish the ability of employers to lower wages in concentrated labor markets. The data, indeed, bear this out. The negative relation between the HHI labor market concentration measure and wages is significantly weaker among plants in industries with high unionization rates. In industries with unionization rates near zero, the elasticity between wages and HHI is approximately –0.015, while in contrast, at the average unionization rate, the elasticity between wages and local-level labor market concentration wages declines by between 29 and 45 percent, depending on the specification.

Fifth, we investigate how local-level labor market concentration affects the transmission of productivity growth into higher wages. We hypothesize that high levels of employer concentration impede the translation of productivity growth to wage increases, as employers use their monopsony power to avoid wage increases. In contrast, when labor markets are more competitive, productivity increases should give rise to wage growth as employers compete for workers. Put differently, productivity growth should translate into a rise in wages when employee bargaining power is sufficiently high.

Measuring labor productivity at the establishment level using census data, we first confirm a link between wage growth and productivity growth, measured at an annual frequency (see, for example, Stansbury and Summers 2017). Importantly, consistent with our hypothesis on the role of monopsony power in labor markets, we find that the link between wage growth and productivity growth is larger when local-level employer concentration is low. Using commuting zones to define local-level employer concentration, the results show that decreasing the employer-based HHI measure of concentration by one standard deviation from its mean is associated with an increase of between 11.2 percent and 18 percent in the elasticity of wages to productivity.[8]

Our sixth result investigates the impact of increased trade with China—the "China shock"—on the level of local labor market concentration. In contrast to our prior findings, in this analysis we focus on the determinants, rather than the effects, of labor market concentration. We hypothesize that by causing employers to shut down a fraction of their operations, increased import competition from China may have led to an increase in local labor market concentration. This is indeed confirmed in the data: a one-standard deviation rise in industry-level import exposure from China is associated with an increase of approximately 3.5 percent in local-level employer concentration. Aside from labor displacement and an associated decline in wages due to reduced labor demand, increased import competition from China may thus have an additional effect of reducing wages of *nondisplaced* workers due to an increase in employer concentration.

This work relates to a growing literature dealing with monopsony in labor markets.[9] As explained above, most prior empirical work on monopsony power and the ability of firms to reduce wages is either indirect (for example, the literature analyzing the employment impact of minimum wage increases) or concentrated on certain occupations or industries. In contrast to these studies, we provide a direct measure of the degree of local-level labor market competition and relate it to wage behavior on a host of margins. Our study is thus most closely related to work by Azar, Marinescu, and Steinbaum (2022), who use online job postings from the website CareerBuilder.com to construct a local-level measure of employer concentration based on commuting zones and occupations.

The main finding of Azar, Marinescu, and Steinbaum (2022) is that increased local-level labor market concentration within a given occupation and commuting zone predicts lower online wage postings. Though related, the two papers are differentiated along a number of important dimensions. We use *actual* wages (at the establishment level) as taken from the Census Bureau, whereas they analyze wage *postings* offered by firms. Our study uses a series of data that span more than three decades and cover the entire manufacturing sector, whereas Azar, Marinescu, and Steinbaum (2022) examine online wage posting within CareerBuilder.com (that is, not solely focused on manufacturing) over a relatively short time (2009–2012). Further, because our study focuses on manufacturing, we can control directly for productivity—an important covariate when analyzing wages—at the establishment–year level. Last, and most importantly, we provide novel evidence on the time-series evolution of the effect of employer concentration, the impact of unionization on the relation between local

8. In related work, Benmelech, Bergman, and Kim (2017) show that the relation between wage growth and productivity growth is increasing in unionization rates. Consistent with the results above, when worker bargaining power rises, increased productivity translates into wage growth.

9. For reviews, see Boal and Ransom (1997) and Council of Economic Advisers (2016).

employer concentration and wages, how labor market concentration affects the transmission of productivity changes into wage growth, and the impact of mergers on local-level concentration and wages.

An additional difference of note between the two papers pertains to the elasticity of wages to local-level employer concentration. Whereas over the last decade in the sample (2008–2016), the ordinary least squares (OLS) elasticity found in the present study is approximately –0.02, in Azar, Marinescu, and Steinbaum (2022) the elasticity (estimated over the 2009–2012 time period) is larger in magnitude and equal to –0.038. Similarly, in their IV specification, Azar, Marinescu, and Steinbaum (2022) find an elasticity of (posted) wages to local-level employer concentration of –0.127, while our IV results show an elasticity that is between –0.03 and –0.06, depending on the specification. As the studies and the employed data sets differ along a host of dimensions—sample period, industries analyzed, online posted wages versus average wages at the establishment—the difference between estimated elasticities is a topic for future research.

Rinz (2022) analyzes the relation between local labor market concentration and wages using the IV methodology in Azar, Marinescu, and Steinbaum (2022). Similar to Azar, Marinescu, and Steinbaum (2022) and our results, Rinz (2022) finds a negative relation between wages and employer concentration. Our work also relates to the growing literature on increased market concentration within industries in the United States (see, for example, Barkai 2020; Autor et al. 2017; De Locker and Eeckhout 2017; Gutiérrez and Philippon 2017) and the relation between such concentration, firm markups, and the labor income share. Whereas this literature focuses on the decrease in competition within the *product* market and the negative relation between product market competition and the labor share, we focus on concentration within the market for *labor*—that is, the ability of monopsonist employers in the corporate sector to exploit their local-level market power to reduce wages.

The rest of the article is organized as follows. Section II presents the data and summary statistics. Section III presents the empirical analysis, and Section IV concludes.

II. Data and Key Variables

A. Data Sources and Sample Construction

1. Plant-level data

To construct measures of wages and labor productivity we obtain data on manufacturing establishments ("plants") from the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM) maintained by the U.S. Census Bureau. The CMF covers all manufacturing plants in the United States for years ending in the digits 2 and 7 ("census years"), resulting in roughly 300,000 plants in each census. The ASM covers approximately 50,000 plants for non-census years. The ASM includes all plants with more than a threshold number of employees, with this threshold increasing from 250 to 1,000 during our sample period.[10] Plants with fewer employees are sampled randomly, with the probability of inclusion increasing in size. Although the ASM is called a survey,

10. The thresholds are 250 employees before 1999, 500 for 1999–2003, and 1,000 after 2003.

reporting is mandatory if the plant is selected, and misreporting is subject to legal penalties and fines. Both databases provide operating information at the plant level, including the total value of shipments, wages, labor hours, and material and energy costs. A key advantage of the CMF and ASM data over standard firm-level databases of public firms, such as Compustat, is that they comprise both privately and publicly owned plants, covering a significant fraction of U.S. workers.

We also use the Longitudinal Business Database (LBD) to construct measures of local-level employer concentration, as described below. The LBD is a comprehensive data set of manufacturing and nonmanufacturing establishments in the United States, tracking more than 5 million establishments per year. The data set provides plant-level number of employees, annual payroll, industry classification, and geographic location (for example, counties and states). We use the LBD rather than the ASM and CMF data to construct measures of labor market concentration since the LBD tracks nearly the entire population of establishments at a yearly frequency. In contrast, the ASM tracks a varying subset of plants over time (due to random sampling), while the CMF is constructed at only a five-year frequency.

In our analysis we also use a set of common control variables standard among research analyzing plant-level data employing the CMF and ASM data sets (see, for example, Schoar 2002). Specifically, firm size is measured by the log number of plants of a given firm, while firm segment size, defined at the firm–industry level, is measured by the log number of plants belonging to the firm in a given industry. Plant age is defined as the number of years since a plant's inception—identified by the flag for plant inception in the LBD—or its first appearance in the CMF or ASM database, whichever is the earliest. The starting year is censored in 1972 when the coverage of the census databases begins.

We require each plant observation to have variables necessary to estimate average wages, labor productivity, and labor value added. Specifically, we require that plant observations include information on total value of shipments, production-worker equivalent hours, total wages, number of employees (both production and nonproduction), and material and energy costs.[11] Because our identification strategy relies on within-firm variation in wages and employer concentration across plants, we require that firm–years have at least two plants under their ownership. In addition, we require that each plant–year have a one-year lagged observation, which is needed to compute changes in average wages and productivity in part of our analysis. Our selection procedure yields approximately 946,000 plant–years over the sample period 1978–2016.[12]

2. *Measuring employer concentration, wages, and labor productivity*

As our main measure of local employer concentration we use the Herfindahl–Hirschman index (HHI) of firm employment in a given industry and at a local labor market. Since there is no clear definition of what constitutes the geographic boundaries of a local labor

11. The ASM and CMF databases provide SIC codes until 2002 and NAICS codes thereafter. We impute SIC codes after 2002.

12. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

market we define our measure as either the county–industry–year level or the commuting zone–industry–year level.[13]

Using the LBD data we first measure the employment share of every firm in a given county or commuting zone and industry year cell as: $s_{f,j,c,t} = \frac{emp_{f,j,c,t}}{\sum_{f=1}^{N} emp_{f,j,c,t}}$, where $emp_{f,j,c,t}$ represents total employment of firm f in industry j in county (or commuting zone) c in year t. We calculate the local-level HHI as the sum of the squared employment shares at the country or commuting zone industry–year level: $HHI_{j,c,t} = \sum_{f=1}^{N} s_{f,j,c,t}^2$. We construct two variants of the employer-concentration HHI measures using either three- or four-digit SIC codes to define industries (thus, four different measures of concentration in total).

We use the log of average wages per worker at the plant–year level as our main dependent variable. Average wages at the plant–year level are calculated as the total wage bill at the establishment divided by its number of workers. We also use labor productivity (per hour) as a control variable, defined as output divided by total labor hours. As is standard, output is computed as the sum of the total value of shipments and the net increase in inventories of finished goods and works in progress. To account for industry-level changes in output price, we divide output by the four-digit SIC-level output price deflator from the NBER-CES manufacturing industry database constructed by Bartelsman, Becker, and Gray (2000). Total labor hours are measured by "production-worker equivalent hours" computed using the ASM and CMF data (as in Lichtenberg 1992; Kovenock and Phillips 1997). Specifically, total labor hours are constructed as the total production-worker hours multiplied by total wages divided by wages for production workers.

3. *Union coverage data*

We construct data on collective bargaining coverage by following the approach in Hirsch and Macpherson (2003).[14] Below we provide a detailed account of the data source and construction that are relevant for our empirical analysis.

We compute the fraction of workers covered by labor unions at the industry-level using the Current Population Survey (CPS) Outgoing Rotation Groups (ORG) data.[15] The resulting data set provides union coverage rate estimates, defined as the number of employees covered by labor unions divided by total employment, by Census Industry Code (CIC) beginning in 1983. Because our plant-level data utilize SIC codes, we match the union coverage data with census plant-level data at the industry level as follows.[16] For the years 1983–2002, we use the 1980 and 1990 U.S. Census Bureau's concordances between CIC codes and SIC codes. For 2003–2016, during which the CIC is based on NAICS codes, we first match 2000 CIC codes to 1990 CIC codes using the U.S. Census

13. In defining local labor markets one issue to note is that, over time, the geographic definition of such markets may vary with changes in the duration of commuting times (stemming, for example, from increased congestion) or with changes in the availability of local transportation.

14. For the data used in Hirsch and Macpherson (2003) see www.unionstats.com (accessed October 30, 2020).

15. The database is available at http://www.nber.org/data/morg.html (accessed October 30, 2020).

16. The CPS ORG data employ the 1980 CIC classification (based on SIC codes) for 1983–1991, the 1990 CIC classification for 1992–2002 (based on SIC codes), and the 2000 CIC (based on NAICS codes) from 2000 onward.

Bureau's concordance and then use the Census Bureau's concordance between 1990 CIC and SIC codes to match with the census plant-level data.[17]

Our analysis focuses on manufacturing plant–year observations in the ASM and CMF databases for 1978–2016 (the first and last years of data coverage). Given that our industry-level database on union coverage begins in 1983, while our sample period starts in 1978, we impute the rate of collective bargaining coverage using 1983 information for years between 1978 and 1982.[18]

B. Descriptive Statistics

Table 1 reports descriptive statistics for the characteristics of the plant observations over the period 1978–2016. The average plant in the sample has $97.9 million in total value of shipments ("sales") and approximately 300 employees with an average annual wage of $41,540.[19] The average plant-level log labor productivity is 4.49, while average plant age is 16.5 years. Firms in our sample own on average 50.9 plants, while the average firm segment (defined at the three-digit SIC level) has 15.2 plants. The average union coverage rate for the manufacturing plants in our sample is 19.8 percent.

Focusing on our measures of local-level employer concentration, the mean employer concentration HHI measure defined at the three-digit SIC and county level is 0.520, while the mean four-digit SIC and county-based HHI measure is 0.651. The standard deviation of county-level HHI using the three-digit SIC code classification is 0.347, while using the four-digit SIC code, the standard deviation is 0.338. When we define local-level employer concentration at the commuting zone level, the HHI measures are naturally lower: the mean employer concentration HHIs defined at the three- and four-digit SIC and commuting zone levels are 0.338 and 0.481, respectively, with an associated standard deviation of 0.308 and 0.343. Thus, the data show significant variation in the local-level concentration measure, with a ratio of standard deviation to mean local HHI varying between 0.52 and 0.91, depending on the industry classification used and the geographic classification.

We also define indicator variables that take the value of one in county–industries in which the employer concentration HHI measure equals one, and zero otherwise. These HHI-based indicator variables are designed to capture counties with high monopsony power of one large employer within a given industry. As Table 1 shows, such a high degree of concentration is not uncommon, with 21.1 percent (8.0 percent) of plant–year observations in counties (commuting zones) in which there is only one employer in a given three-digit SIC industry.

Figure 1 plots trends in local-level employer concentration over time, showing that employer concentration has remained relatively stable over the sample period 1978–2016. In Panel A, while the average local-level HHI concentration measure (defined at

17. For the majority of CIC industries used in the CPS, this matching procedure results in direct linkages to three-digit SIC industries. In a minority of cases, the procedure results in a match to a two- or four-digit SIC industry, in which case the finer industry classification is used.

18. The census plant-level datasets use different vintages of SIC and NAICS codes across years (see for example, Table 1 in Fort and Klimek 2018). Thus, we use the appropriate vintage of the industry codes for each year (for example, SIC1997 for 1997).

19. Due to the U.S. Census Bureau's disclosure rules, we do not report variable percentiles.

Table 1
Summary Statistics on Plant Observations from the CMF and ASM Sample

	Mean	SD
Total value of shipment ($m)	97.92	445.90
Total wages ($m)	10.95	35.78
Total employees	299.80	732.50
Total labor hours (000)	717.10	6465.00
HHI (SIC3–county–year)	0.520	0.347
HHI (SIC4–county–year)	0.651	0.338
HHI (SIC3–CZ–year)	0.338	0.308
HHI (SIC4–CZ–year)	0.481	0.343
HHI (SIC3–county–year) = 1	0.211	0.408
HHI (SIC3–CZ–year) = 1	0.080	0.271
Log labor productivity	4.49	0.86
Average wage ($000)	41.54	14.18
Average wage ($000), production	36.82	13.65
log(employment, SIC3–county–year)	6.24	1.61
log(employment, SIC4–county–year)	5.75	1.56
log(employment, SIC3–CZ–year)	7.10	1.63
log(employment, SIC4–CZ–year)	6.40	1.60
Plants per segments (SIC3)	15.17	34.08
Plants per firm	50.88	72.68
Plant age	16.49	10.80
Unionization rate	0.198	0.123
Observations (plant–years)	946,000	

Notes: This table presents descriptive statistics on the manufacturing plant–year observations used in the analysis from the CMF and ASM databases for the period 1978–2016. We require each observation in the sample to have all variables necessary to compute average wages, labor productivity, and value added per worker (and their lagged values). Total value of shipments is TVS in the CMF and ASM databases and a measure of sales from plants in million dollars. Total wage is the sum of wages for production and nonproduction workers in million dollars. Total employees is the number of total employees. Total labor hours is the production worker equivalent human hours in thousands. HHI (SIC3 or 4–county or CZ–year) is the Herfindahl–Hirschman Index (HHI) of employment by firms at the county or commuting zone (CZ)–industry (three- or four-digit)–year level. HHI (SIC3–county or CZ–year) = 1 is an indicator variable equal to one if HHI = 1, and zero otherwise. HHI (SIC3 or 4–year) is the Herfindahl–Hirschman Index (HHI) of employment by firms at the industry (three- or four-digit)-year level. log(employment, SIC3 or 4–county or CZ–year) is the log number of employees at the county or CZ–industry (three- or four-digit)–year level. Labor productivity is defined as output divided by total labor hours (a quantity-based measure of labor productivity). Average wage is computed as total wage divided by total employees (in thousand dollars). Average wage, production is computed as production employee wage divided by total production employees (in thousand dollars). log(employment, SIC3 or 4–county or CZ–year) is the log number of employment at the county or CZ–industry (three- or four-digit)–year level. Plants per segment is the number of plants in a given three-digit SIC industry segment of a given firm. Plants per firm is the total number of plants of a given firm. Plant age is the number of years since a plant's birth, which is proxied either by the flag for plant birth in the Longitudinal Business Database (LBD) or by its first appearance in the CMF or ASM database, whichever is earliest. Unionization rate is the industry-level percentage of the workforce covered by collective bargaining collected from the CPS. The number of observations is rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

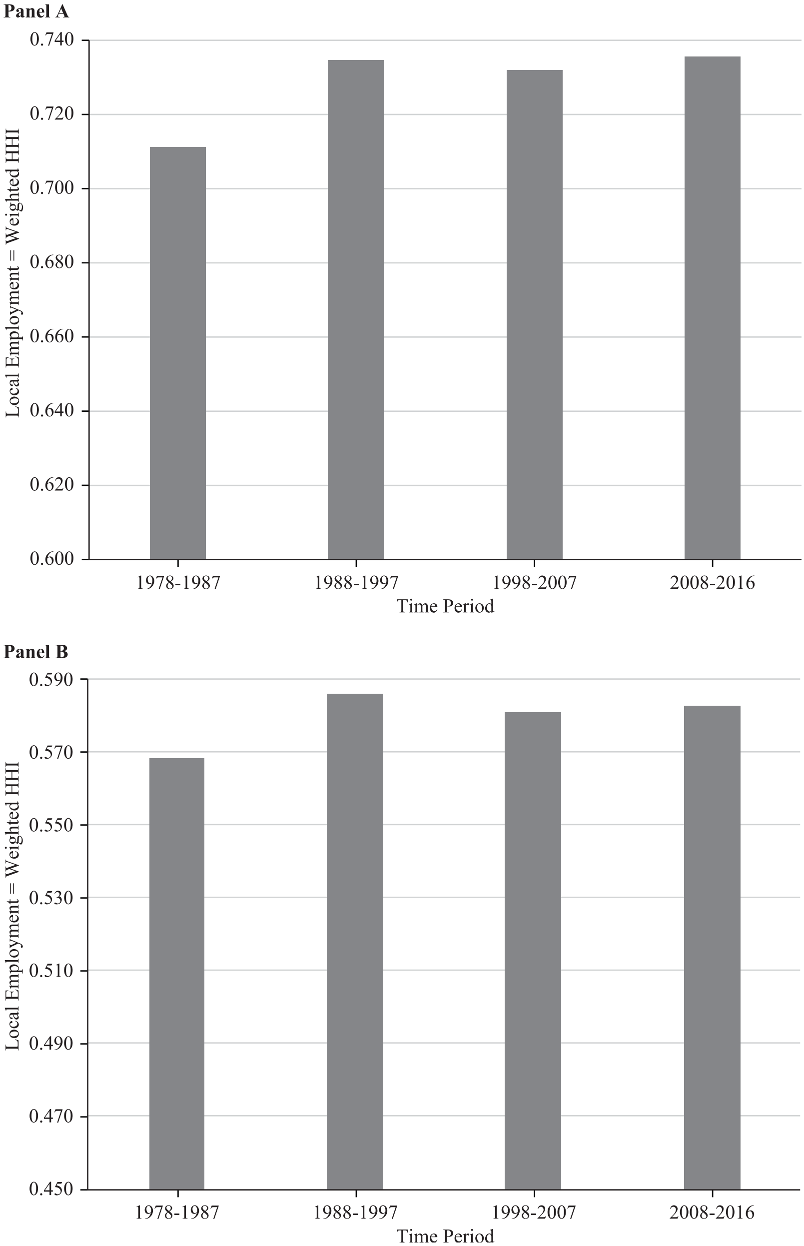

Figure 1

Trends in Average Local-Level Employment Concentration, 1978–2016

Notes: This figure plots trends in the employment-weighted average of the Herfindahl–Hirschman Index (HHI) of employment by firms computed at the county (Panel A) or commuting zone (Panel B) four-digit SIC industry–year level. The computed HHI is averaged across county–four-digit industry–year cells within each of the ten-year periods (the last period includes nine years, 2008–2016) using the number of employees in each cell as weights. Thus, the average HHI represents the degree of employer concentration the average worker faces in the labor market.

the four-digit SIC and county level) increased slightly from 0.712 to 0.735 between 1978–1987 and 1988–1997, it remains around 0.735 in the next two decades.[20] Similarly, Panel B shows that the average local-level HHI concentration measure (defined at the four-digit SIC and commuting zone level) increased from 0.569 to 0.587 in the first two decades—an increase of 3.2 percent—and then remains at a similar level in the next two ten-year periods.[21]

III. Empirical Analysis

A. Relation between Employer Concentration and Wages

We begin by investigating a reduced-form baseline relation between employer concentration and wages. To this end, we run the following regression:

$$\log(avg.\ wages)_{pfjt} = \beta_0 + \beta_1 \log(\mathrm{HHI})_{jct-1} + \beta_2 \mathbf{X}_{pfjt} + \beta_3 \mathbf{Z}_{jct-1} + \boldsymbol{\delta}_{jt} + \boldsymbol{\mu}_{ft} + \varepsilon_{pfjt}, \tag{1}$$

where $\log(avg.\ wages)_{pfjt}$ is log average wages per worker in plant p, owned by firm f, operating within industry j, in year t; $\log(\mathrm{HHI}_{jct-1})$ is the log of one-year lagged employment-based measure of concentration in either county (or commuting zone) c and industry j, defined at either the three- or four-digit SIC level; $\mathbf{X}_{pfjt}$ is a vector of plant-level control variables comprising the log of labor productivity, the log of the number of plants per segment within the firm, the log of the number of plants per firm, and plant age; $\mathbf{Z}_{jct-1}$ is the one-year lagged log of aggregate employment at the county-industry level; $\boldsymbol{\delta}_{jt}$ is a vector of either industry or industry-by-year fixed effects; and $\boldsymbol{\mu}_{ft}$ is a vector of firm or firm-by-year fixed effects. All standard errors are clustered at the county or commuting zone level.

Table 2 provides the results from estimating Equation 1 using either three- or four-digit SIC codes and either county or commuting zone to compute the HHI employment concentration measure. Column 1 of Table 2 includes as explanatory variables year, industry, and firm fixed effects in addition to log employment at the three-digit industry–county level and plant-level controls (labor productivity and plant age), as well as firm- and firm segment–level controls, such as log(plants per segment) and log(plants per firm). The plant-level explanatory variables—in particular, log(labor productivity) and plant age—control for plant-level productivity, alleviating the concern that our results are driven by productivity differences across plants. Further, by including industry and firm fixed effects, we exploit within-firm and within-industry variation of employer concentration to identify the relation between wages and employer concentration. Thus, the estimates in Column 1 are based off of variation in employer concentration across different local labor markets within a given firm and industry.

20. Average employer concentration measures in Figure 1 are calculated at the industry–county or CZ level using industry–county-level (or industry–CZ-level) employment as weights. Thus, the average HHI in Figure 1 represents the degree of employer concentration the average worker faces in the labor market. Summary statistics in Table I do not weigh plant observations by employment.

21. Rinz (2022) finds a declining trend in local labor employer concentration analyzing a sample of all industries in the LBD.

Table 2
Local Employer Concentration and Wages

	Dep. Var.: Log Avg. Wages									
	County					CZ				
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC4 (5)	SIC3 (6)	SIC3 (7)	SIC4 (8)	SIC4 (9)	SIC4 (10)
log HHI (ind–local–year)	−0.010	−0.009	−0.012	−0.011	−0.022	−0.009	−0.010	−0.012	−0.011	−0.008
	−3.16	−3.13	−4.21	−4.14	−4.04	−3.15	−3.17	−3.92	−3.76	−1.85
log(emp, ind–local–year)	0.033	0.032	0.030	0.031	0.034	0.033	0.032	0.031	0.031	0.035
	36.39	34.12	39.91	38.47	14.46	33.29	30.57	35.94	33.41	10.26
log(labor productivity)	0.072	0.069	0.067	0.064	0.154	0.071	0.068	0.066	0.063	0.155
	48.08	41.54	42.88	36.81	51.94	39.9	34.38	35.07	30.54	38.88
log(plants per segment)	−0.007	−0.008	−0.005	−0.007	−0.041	−0.006	−0.007	−0.005	−0.006	−0.043
	−5.08	−5.48	−4.62	−4.77	−21.92	−4.3	−4.65	−4.22	−4.04	−22.17
log(plants per firm)	−0.007		−0.006		0.038	−0.008		−0.007		0.039
	−4.38		−4.29		31.88	−4.46		−4.33		27.84
Plant age (/100)	0.266	0.275	0.257	0.264	0.321	0.285	0.293	0.274	0.281	0.349
	30.57	31.09	29.97	29.68	21.94	30.13	31.46	28.58	28.71	19.51

(*continued*)

Table 2 (*continued*)

	Dep. Var.: Log Avg. Wages									
	County					CZ				
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC4 (5)	SIC3 (6)	SIC3 (7)	SIC4 (8)	SIC4 (9)	SIC4 (10)
Year fixed effects	Y		Y		Y	Y		Y		Y
Industry fixed effects	Y		Y			Y		Y		
Industry–year fixed effects		Y		Y			Y		Y	
Firm fixed effects	Y		Y			Y		Y		
Firm–year fixed effects		Y		Y			Y		Y	
Observations	946,000	946,000	946,000	946,000	946,000	946,000	946,000	946,000	946,000	946,000
R^2	0.571	0.6549	0.5847	0.6728	0.2015	0.5716	0.6556	0.586	0.6741	0.1995

Notes: This table examines the effects of employer concentration in a local labor market on the wages of plants. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(emp) are lagged by one year. Columns 1–5 (Columns 6–10) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 6–5 (Columns 3–5 and 8–10) present estimates using three- and four-digit SIC industries to compute HHI, log(employment), and log(plants per segment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

As Column 1 of Table 2 shows, the coefficient estimate for log(employment) is 0.033 and statistically significant at the 1 percent level, suggesting that wages are higher in local labor markets with more workers. This finding is consistent with economic forces related to agglomeration (for example, Ellison, Glaeser, and Kerr 2010; Greenstone, Hornbeck, and Moretti 2010). As would be expected, the coefficient on log labor productivity is positive (equal to 0.072 and significant at the 1 percent level), indicating a positive relation between productivity and wages.

Turning to our main variable of interest, log(HHI), and still focusing on Column 1, the results indicate a negative relation between wages and local-level employer concentration calculated at the county level. The elasticity of wages to local-level HHI is –0.01, with the relation between log(wages) and log(HHI) statistically significant at the 1 percent level. The wage-to-HHI elasticity implies that moving from one standard deviation below to one standard deviation above the mean-level HHI is associated with a decrease of 1.6 percent in wages.[22] Thus, consistent with the hypothesis that labor market monopsony power detrimentally affects wages, the data show that wages are negatively related to the degree of employer concentration in the local labor market. We lag log(HHI) by one year since it may take time for labor market monopsony power to affect wages. Our results are not sensitive to this modeling choice, and we obtain similar results when using contemporaneous log(HHI) in our regressions (Appendix 1 Table A1).

While the fixed effects in Column 1 mitigate the concern that lower wages in more concentrated labor markets are due to heterogeneity across firms, an additional concern is that the negative association between local employer concentration and wages is driven by omitted differences across different industries within firms in a given year. For example, a firm may have a more productive industry segment (for example, machinery) in a less concentrated local labor market, and a less productive segment (for example, chemicals) in a more concentrated market, which may lead to a spurious correlation between concentration and wages due to differences in productivity levels. To address this concern, in Column 2 of Table 2 we include both firm-by-year fixed effects as well as industry-by-year fixed effects, which absorb time-varying industry-level shocks. In this analysis the identifying variation stems from plants operating in the same industry and belonging to the same firm located in different counties with varying levels of employer concentration.

As can be seen in Column 2, the elasticity of wages to employer concentration remains virtually unchanged at –0.009 and significant at the 1 percent level. Thus, comparing plants in the same industry and firm in a given year, we find that those located in a more concentrated local labor market pay lower wages. Moving from one standard deviation below to one standard deviation above the mean-level HHI is associated with a 1.5 percent decline in wages. Columns 3 and 4 repeat the analysis in Columns 1 and 2 using an industry definition that is based on four-digit SIC codes and yield similar estimates to those in Columns 1 and 2. Our identification strategy hinges on the use of within-firm variation—hence, we use either firm or firm–year fixed effects. However, we also report results from estimating Equation 1 without firm or industry fixed effects in Column 5 and find an elasticity of wages to employer concentration of –0.022.

22. Interquartile movements are not reported as census rules prohibit disclosure of distribution percentiles.

Columns 6–10 of Table 2 repeat the analysis in Columns 1–5 using commuting zones—instead of counties—to compute the HHI measure of employer concentration. Indeed, commuting zones are constructed such that, "CZs…are geographic units of analysis intended to more closely reflect the local economy where people live and work…These commuting zones…are intended to be a spatial measure of the local labor market."[23] The negative relation between concentration and employee wages is evident when we use commuting zones to define local labor markets as well. The estimated elasticities in Columns 5–8 imply that moving from one standard deviation below to one standard deviation above the mean-level HHI is associated wages that are lower by between 2.0 percent and 2.9 percent.

To further alleviate the concern that industry-level heterogeneity (in productivity in particular) is driving the relation between employer concentration and wages, we focus our estimation on a subsample of firms that operate multiple plants within a *single* industry segment (with industries defined at either the three- or four-digit SIC level). Combined with firm-by-year fixed effects, using this subsample removes cross-industry variation within firms, thereby sidestepping cross-industry heterogeneity as an alternative channel that drives wage differences.[24]

Table 3 presents the results from estimating Equation 1 using a subsample of firms that operate multiple plants within a single industry segment, defined at the three- or four-digit SIC level. As Table 3 illustrates, across all columns the coefficient on the employer concentration HHI measure is negative and significant at the 1 percent level, consistent with the baseline result in Table 2. The economic magnitude is larger than that exhibited in Table 2, indicating that the effect is larger among the subset of firms that are unlikely to be affected by cross-industry heterogeneity in productivity and wages. For example, when we define local labor markets at the commuting zone and three-digit SIC level, the effect of moving from one standard deviation below to one standard deviation above the mean-level HHI is associated with a 5.1 percent decline in wages.

In sum, our results are robust to the inclusion of industry-by-year fixed effects and hold in multiple-plant, single-industry firms, thus alleviating concerns that industry-level heterogeneity is driving the negative relation between employer concentration and wages. While we focus our analysis on the manufacturing sector to control for productivity in our wage regressions, we expect our results to hold in other industries that also exhibit employer concentration. Indeed, Rinz (2022) confirms the negative relation between earnings and employer concentration in other industries in the United States, while Abel, Tenreyro, and Thwaites (2018) confirm a similar negative relation for a wide sample of firms in the United Kingdom.

B. Robustness Tests—Labor Productivity and National-Level Concentration

1. Controlling for labor value added

One concern regarding the negative relation between employer concentration and wages presented in our baseline results is that the local-level HHI measure is correlated with labor productivity, implying that the results may be capturing the effect of low productivity,

23. https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/ (accessed October 30, 2020).

24. Since our measures of plant-level productivity may be driven by the degree of local competition, we also estimate the regressions without plant-level controls and obtain similar results (Appendix 1, Table A2).

Table 3
Subsample of Firms with One Industry Segment across Multiple Plants

	Dep. Var.: Log Avg. Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
log(HHI, ind–local–year)	−0.012	−0.011	−0.014	−0.011	−0.017	−0.017	−0.018	−0.017
	−3.57	−2.97	−4.44	−3.31	−4.21	−3.50	−4.53	−3.42
log(emp, ind–local–year)	0.028	0.029	0.028	0.031	0.026	0.027	0.027	0.029
	22.28	19.50	22.32	19.70	19.15	16.08	19.16	16.78
log(labor productivity)	0.047	0.041	0.042	0.036	0.046	0.040	0.041	0.035
	15.33	9.78	12.51	7.71	13.10	8.56	11.19	7.25
log(plants per segment)	0.002		0.006		0.001		0.004	
	0.32		0.78		0.08		0.48	
log(plants per firm)	−0.013		−0.014		−0.012		−0.012	
	−1.88		−1.94		−1.66		−1.72	
Plant age (/100)	0.359	0.371	0.362	0.373	0.373	0.384	0.378	0.390
	29.30	25.20	27.53	23.77	29.02	24.76	27.28	23.23

(*continued*)

Table 3 (*continued*)

	Dep. Var.: Log Avg. Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
Year fixed effects	Y		Y		Y		Y	
Industry fixed effects	Y		Y		Y		Y	
Industry–year fixed effects		Y		Y		Y		Y
Firm fixed effects	Y		Y		Y		Y	
Firm–year fixed effects		Y		Y		Y		Y
Observations	226,000	226,000	187,000	187,000	226,000	226,000	187,000	187,000
R^2	0.6348	0.7423	0.6463	0.7523	0.6352	0.7430	0.6469	0.7531

Notes: This table examines the effects of employer concentration in a local labor market on the wages of plants using a subsample of plants owned by firms that have multiple plants in only one industry segment. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(employment) are lagged by one year. Columns 1–4 (Columns 5–8) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute HHI, log(employment), and log(plants per segment). The t-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

Table 4
Local Employer Concentration and Wages Controlling for Labor Value Added

	Dep. Var.: Log Avg. Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
log(HHI, ind–local–year)	−0.010	−0.009	−0.013	−0.011	−0.010	−0.010	−0.012	−0.012
	−3.28	−3.24	−4.34	−4.25	−3.26	−3.24	−4.02	−3.83
log(emp, ind–local–year)	0.032	0.032	0.030	0.031	0.032	0.032	0.030	0.031
	36.10	33.92	39.44	38.15	33.13	30.46	35.52	33.17
log(labor productivity)	0.062	0.060	0.057	0.056	0.061	0.059	0.057	0.054
	36.18	30.69	31.69	26.94	30.24	25.91	25.82	22.74
log(labor VA)	0.011	0.010	0.010	0.009	0.011	0.010	0.011	0.009
	15.59	12.69	15.26	11.38	16.17	13.01	15.25	11.72
log(plants per segment)	−0.007	−0.008	−0.006	−0.007	−0.006	−0.007	−0.005	−0.006
	−5.12	−5.46	−4.75	−4.83	−4.33	−4.64	−4.33	−4.10
log(plants per firm)	−0.007		−0.006		−0.008		−0.007	
	−4.50		−4.38		−4.58		−4.41	
Plant age (/100)	0.265	0.274	0.256	0.263	0.284	0.291	0.273	0.280
	30.43	30.98	29.84	29.58	30.00	31.37	28.45	28.60

(continued)

Table 4 (*continued*)

	Dep. Var.: Log Avg. Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
Year fixed effects	Y		Y		Y		Y	
Industry fixed effects	Y		Y		Y		Y	
Industry–year fixed effects		Y		Y		Y		Y
Firm fixed effects	Y		Y		Y		Y	
Firm–year fixed effects		Y		Y		Y		Y
Observations	946,000	946,000	946,000	946,000	946,000	946,000	946,000	94,6000
R^2	0.5715	0.6552	0.5850	0.6730	0.5720	0.6559	0.5864	0.6743

Notes: This table examines the effects of employer concentration in a local labor market on the wages of plants including an additional control for labor productivity—valued added (total value of shipments + net increase in inventories of finished goods and works in progress—material and energy costs) scaled by labor hours. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(employment) are lagged by one year. Columns 1–4 (Columns 5–8) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute HHI, log (employment), and log(plants per segment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau’s disclosure rules.

rather than employer concentration, on wages. Although all regressions control for the log of labor productivity (defined as the natural log of output scaled by labor hours), this variable may still be an imperfect control for actual labor productivity. To alleviate this concern, in Table 4 we add to the regression specification an additional control variable for labor productivity—namely, value added (VA) by labor. As is standard, value added is defined as the total value of shipments plus the net increase in inventories of finished goods and works in progress minus material and energy costs scaled by total labor hours, with all components deflated using four-digit SIC industry-level deflators (available from the NBER-CES manufacturing database). One key difference of labor value added relative to our labor productivity measure is that the former nets out intermediate inputs (that is, material and energy), which are presumably not affected by labor inputs.

Table 4 shows that in all specifications the coefficient on log(labor VA) is positive and significant at the 1 percent level, consistent with the notion that employees of plants who add more value per labor hour are paid more. Importantly, the coefficients on the local-level HHI measure of employer concentration remain statistically significant, and their magnitudes are almost identical to those found in Table 2.

2. *Controlling for national-level employer concentration*

Autor et al. (2017) show that product markets in the United States have become more concentrated in the past few decades, giving rise to "superstar firms" that are highly productive yet have lower labor shares of income. Related to these findings, one concern regarding our results is that if product market concentration—commonly defined at the national level for traded sectors such as manufacturing—and local labor market concentrations are positively correlated, then the negative association between local employment concentration and wages may merely reflect a negative relation between (national) product market concentration and labor shares.

In response to this concern, we note first that as part of our identification strategy we include firm-by-year fixed effects. As such, the identification exploits within-firm–year variation across plants belonging to the same firm. This speaks against the hypothesis that our results are driven by heterogeneity across firms, as, for example, implied by the existence of "superstar firms." To further alleviate this concern, we proxy for national-level product market competition by constructing our employer HHI concentration measures at the national level. We first measure the employment share of every firm in a given industry-year cell as: $s_{f,j,t} = \frac{emp_{f,j,t}}{\sum_{f=1}^{N} emp_{f,j,t}}$, where $emp_{f,j,t}$ represents total employment in firm f operating in industry j in year t. We next calculate the industry–year HHI as the sum of the squared employment shares: $\text{HHI}_{j,t} = \sum_{f=1}^{N} s_{f,j,t}^2$. As with the local-level HHI, we define two variants of the national-level HHI using either three- or four-digit SIC codes. We then include the national-level HHI as a proxy for product market concentration in Equation 1.

Table 5 shows that the coefficient on national-level HHI (calculated using either three-digit or four-digit SIC codes) is positive and statistically significant in Columns 2–4, inconsistent with the alternative explanation that high levels of national-level employer concentration are associated with lower wages. Importantly, even with the inclusion of the national HHI measure of employer concentration, the coefficient on the local HHI remains negative with slightly higher magnitudes than those found in Table 2.

Table 5
Local Employer Concentration and Wages Controlling for National Concentration

	Dep. Var.: Log Avg. Wages			
	County		CZ	
	SIC3 (1)	SIC4 (2)	SIC3 (3)	SIC4 (4)
log(HHI, ind–local–year)	–0.010	–0.013	–0.010	–0.012
	–3.16	–4.27	–3.19	–4.04
log(HHI, ind–year)	0.002	0.005	0.004	0.007
	1.17	3.21	2.06	4.62
log(emp, ind–local–year)	0.033	0.030	0.033	0.030
	36.33	39.81	33.13	35.45
log(labor productivity)	0.072	0.067	0.071	0.067
	48.17	42.91	40.08	35.15
log(plants per segment)	–0.007	–0.006	–0.006	–0.005
	–5.09	–4.72	–4.36	–4.35
log(plants per firm)	–0.007	–0.006	–0.008	–0.007
	–4.45	–4.42	–4.55	–4.51
Plant age (/100)	0.266	0.257	0.285	0.274
	30.56	29.97	30.13	28.6
Year fixed effects	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Observations	946,000	946,000	946,000	946,000
R^2	0.5711	0.5847	0.5716	0.5860

Notes: This table examines the effects of employer concentration in a local labor market on the wages of plants, including an additional control for employer concentration at the national level. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(employment) are lagged by one year. Columns 1–4 (Columns 5–8) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute HHI, log(employment), and log(plants per segment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

C. Using Mergers and Acquisitions to Instrument for Local Employer Concentration

Our results thus far document a negative relation between local employer concentration and wages. In order to better identify the link between employer concentration and wages, our results rely on within-firm or within-firm-by-year variation, controlling for cross-industry heterogeneity and plant-level productivity. In this section, we attempt to further alleviate omitted-variable concerns by employing an instrumental variable (IV) approach. Following previous literature identifying mergers and acquisitions (M&As) as a key driver of increased concentration and market power of firms in a given industry (for example, Kim and Singal 1993; Grullon, Larkin, and Michaely 2019; Naidu, Posner, and Weyl 2018), we use M&A activity as an IV for local labor market concentration. We focus on M&As because ordinary plant openings and closings (which may affect local employer concentration) are likely driven by local economic conditions, which in turn have a direct effect on wages. In contrast, M&A activity and the plant ownership switches entailed, enable us to exploit variation in plant ownership and concentration that is not driven by plant openings or closings.

Before moving to our main IV analysis, we demonstrate the endogeneity problem of using plant openings and closings to measure concentration by regressing the number of plant openings and closings on local economic conditions. Using the census LBD we define dependent variables as the number of plant openings and closings at the three- or four-digit SIC industry–county–year level for 1978–2015. Next we match these industry–county–year observations to the one-year-lagged county-level unemployment-to-population ratio and log median household income. We estimate the following regression:

$$(2)\quad \log(1+\#\ \textit{of plant openings or closures})_{jct} = \beta_0 + \beta_1 \mathbf{X}_{ct-1} + \boldsymbol{\delta}_{jc} + \boldsymbol{\mu}_t + \varepsilon_{jct},$$

where $log(1+\#\ \textit{of plant openings or closures})_{jct}$ is the log (1+ number of plant openings or closures) in industry j defined at either the three- or four-digit SIC level, in county c, in year t; $\mathbf{X}_{ct-1}$ is the one-year lagged unemployment-to-population ratio and log median household income in county c; $\boldsymbol{\delta}_{jc}$ is a vector of industry-by-county fixed effects; and $\boldsymbol{\mu}_t$ is a vector of year fixed effects. All standard errors are clustered at the county level.

Table 6 reports the regression estimates of Equation 2, with the analysis using either levels (odd numbered columns) or first differences (even numbered columns) of the local economic condition variables described above. Columns 1–4 show that the lagged county-level unemployment-to-population ratio is significantly negatively associated with the number of plant openings in a given industry–county. On the other hand, lagged county-level unemployment-to-population ratio is significantly positively associated with the number of plant closings (Columns 5–8). The coefficient on the log median household income is largely insignificant, except for in Column 6.

To construct our instrument, we use the annual information on plant ownership within the LBD data. Defining M&A activity using cases in which plant ownership switches from one firm to another, our identification strategy focuses on plant ownership changes between two firms, each of which operated at least one plant in the local labor market one year prior to the merger. Since prior to the merger both acquirer and seller firms operated plants in the local labor market, the switch in plant ownership shifts local-level employer concentration. Moreover, by focusing on M&A activity of firms that had *existing* plants in the local labor market before the merger, we are able to exploit variation in plant ownership and concentration, which is not driven by plant openings or closings. To avoid a weak instruments problem, we require that the combined employment share of both the acquiring and selling firms in the local labor market exceeds a threshold of either 5 percent or 10 percent, one year prior to the merger.

We instrument the five-year change in local-level log(HHI) using lagged measures of M&A activity in a given local labor market. To this end, we define a set of instruments

Table 6
Local Economic Conditions and Plant Opening or Closure

	Dep. Var.: Log # Plant Openings				Dep. Var.: Log # Plant Closures			
	SIC3 Level (1)	SIC3 Diff. (2)	SIC4 Level (3)	SIC4 Diff. (4)	SIC3 Level (5)	SIC3 Diff. (6)	SIC4 Level (7)	SIC4 Diff. (8)
Unemp–pop. ratio, [t – 1]	–0.422	–0.229	–0.178	–0.143	0.215	0.682	0.287	0.558
	–8.15	–5.78	–5.15	–4.28	3.75	14.71	6.12	14.12
log(median HH income), [t – 1]	0.004	0.000	–0.002	0.000	0.011	–0.002	0.005	–0.001
	0.77	0.05	–0.96	–0.03	1.49	–2.04	1.20	–1.41
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry–county fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,340,000	3,340,000	4,830,000	4,830,000	3,340,000	3,340,000	4,830,000	4,830,000
R^2	0.3868	0.3867	0.3306	0.3306	0.4601	0.4601	0.3935	0.3936

Notes: This table examines the relation between local economic conditions and plant opening and closure using a sample of industry–county–year observations constructed using the LBD. In Columns 1–4 (Columns 5– 8), the dependent variable is the log (one plus) number of plant openings or closures in a given industry–county–year cell. Local economic conditions are proxied for by the one-year-lagged unemployment-to-population ratio and log median household income, either in level (odd-numbered columns) or first-difference (even-numbered columns). Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute the log number of plant openings or closures. The t-statistics based on standard errors adjusted for sample clustering at the county level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau’s disclosure rules.

based on the log number of plants (or alternatively the log number of employees) involved in M&A transactions in a given year, industry, and either county or commuting zone. Plant involvement in M&A activity is defined by plant ownership switches as explained above. We then use instrumented changes in local-level employer concentration to predict log changes in wages, after controlling for industry-by-year fixed effects and changes in a vector of plant- and local-level characteristics. Specifically, we run the following regressions:

$$(3) \quad \Delta \text{logHHI}_{jct-5\rightarrow t} = \beta_0 + \beta_1^k \sum_{k=1}^{5} \text{M\&A}_{jct-k} + \beta_2 \Delta \mathbf{X}_{pfjt-5\rightarrow t} + \beta_3 \Delta Z_{jct-5\rightarrow t} + \boldsymbol{\delta}_{jt} + \varepsilon_{pfjt}$$

$$(4) \quad \Delta \log\,(avg.\ wages)_{pfjt-5\rightarrow t} = \beta_0 + \beta_1 \Delta \widehat{\text{logHHI}}_{jct-5\rightarrow t} + \beta_2 \Delta \mathbf{X}_{pfjt-5\rightarrow t} + \beta_3 \Delta Z_{jct-5\rightarrow t} + \boldsymbol{\delta}_{jt} + \nu_{pfjt}$$

where $\Delta\text{logHHI}_{jct-5\rightarrow t}$ is the change in the log measure of concentration in either county or commuting zone c and industry j (defined at the three-digit SIC level), from year $t-5$ to year t; $\text{M\&A}_{jct-k}$ is either the log number of plants or the log number of employees involved in M&As in industry j and county or commuting zone c, k years prior to year $t\,(1 \le k \le 5)$, with plant involvement in M&A activity defined by plant ownership switches; $\Delta\log(\text{avg. wages})_{pfjt-5\rightarrow t}$ is the change in log average wages per worker in plant p, owned by firm f, operating within industry j; $\Delta \mathbf{X}_{pfjt-5\rightarrow t}$ is a vector of plant-level control variables that include: changes in log of labor productivity, the log of the number of plants per segment within the firm, and the log of the number of plants per firm, all from year $t-5$ to year t; $\mathbf{Z}_{jct-5\rightarrow t}$ is the change in log of aggregate employment at the county-industry or at the commuting zone and industry level; and $\boldsymbol{\delta}_{jt}$ is a vector of industry-by-year fixed effects (defined at the two-digit SIC level). All standard errors are clustered at either the county or community zone level. Our sample for the IV analysis includes approximately 467,000 plant–year observations with five years of lagged M&A measures for 1983–2016.

The main identifying assumption underlying our identification is that plant acquisitions impact local-level wages only through their effect on local labor market concentration. We attempt to alleviate endogeneity concerns by constructing our IV on the basis of mergers that are potentially driven by strategic considerations and are not necessarily related to local labor market conditions or plant level characteristics. To the extent that a merger is driven by local economic conditions, this identification assumption is clearly problematic. IV estimates should thus be interpreted with caution given the potential endogenous nature of the merger itself.

Panel A of Table 7 reports the first-stage regression results. Column 1, which uses counties to define the local market and the log number of plants involved in M&As as the instrument, shows that the coefficient estimates for the instruments, $\text{M\&A}_{t-k}$ $(1 \le k \le 5)$, are positive and statistically significant at the 1 percent level. Thus, as expected, when more plants are affected by M&As in the prior five years, employment concentration in local labor markets rises. The economic magnitude of the relation between the instruments and changes in HHI is sizable—for example, the elasticity of changes in HHI over the previous five years to the number of plants involved in mergers in year $t-1$ is 0.229. In addition, the coefficient and level of significance on the lagged instruments $\text{M\&A}_{t-k}$ generally increases as the timing of the instrument moves closer to

Table 7
Local Employer Concentration and Wages: Instrumental Variables Estimates Using Mergers and Acquisitions

	Dep. Var.: ΔlogHHI (ind–local–year)$_{t-5\rightarrow t}$							
	SIC3							
	5% Market Share Threshold				10% Market Share Threshold			
	County		CZ		County		CZ	
M&A: (log *N* merged)	Plants (1)	Emp. (2)	Plants (3)	Emp. (4)	Plants (5)	Emp. (6)	Plants (7)	Emp. (8)
Panel A: First Stage								
M&A$_{t-1}$	0.229	0.037	0.201	0.035	0.330	0.049	0.317	0.051
	15.33	12.20	11.45	12.04	15.69	15.35	14.21	15.20
M&A$_{t-2}$	0.203	0.033	0.190	0.032	0.299	0.044	0.295	0.047
	10.19	13.13	13.26	13.63	15.61	14.91	12.69	15.97
M&A$_{t-3}$	0.179	0.031	0.163	0.030	0.264	0.039	0.226	0.039
	8.95	11.89	11.85	14.48	12.29	12.51	8.00	13.25
M&A$_{t-4}$	0.154	0.027	0.136	0.025	0.226	0.033	0.185	0.035
	8.11	10.10	8.70	10.72	8.62	8.40	5.57	11.17
M&A$_{t-5}$	0.182	0.031	0.147	0.028	0.275	0.040	0.200	0.038
	7.37	10.88	6.94	11.03	7.58	8.68	4.50	10.90

(*continued*)

Table 7 (*continued*)

	Dep. Var.: ΔlogHHI (ind–local–year)$_{t-5\to t}$							
	SIC3							
	5% Market Share Threshold				10% Market Share Threshold			
	County		CZ		County		CZ	
M&A: (log N merged)	Plants (1)	Emp. (2)	Plants (3)	Emp. (4)	Plants (5)	Emp. (6)	Plants (7)	Emp. (8)
Δlog(emp, ind–local–year)$_{t-5\to t}$	−0.167	−0.167	−0.214	−0.214	−0.167	−0.167	−0.214	−0.214
	−28.13	−28.07	−23.48	−23.47	−28.01	−28.02	−23.39	−23.36
Δlog(labor productivity)$_{t-5\to t}$	−0.010	−0.010	−0.010	−0.010	−0.010	−0.010	−0.010	−0.010
	−6.02	−6.03	−4.85	−4.82	−5.97	−5.96	−4.78	−4.81
Δlog(plants per segment)$_{t-5\to t}$	−0.006	−0.007	−0.002	−0.002	−0.006	−0.006	−0.002	−0.002
	−2.54	−2.61	−0.94	−1.00	−2.54	−2.53	−0.65	−0.67
Δlog(plants per firm)$_{t-5\to t}$	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
	5.29	5.3	5.83	5.88	5.3	5.31	5.94	5.97
Industry–year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
F-stat	53.79	55.70	40.14	51.49	65.22	66.47	50.81	69.72
Observations	468,000	468,000	468,000	468,000	468,000	468,000	468,000	468,000
R^2	0.0939	0.0948	0.1045	0.1061	0.0936	0.0937	0.1027	0.1037

(*continued*)

Table 7 (*continued*)

	Dep. Var.: $\Delta\log(Avg.\ Wages)_{t-5\rightarrow t}$							
	SIC3							
	5% Market Share Threshold				10% Market Share Threshold			
	County		CZ		County		CZ	
M&A: (log *N* merged)	Plants (1)	Emp. (2)	Plants (3)	Emp. (4)	Plants (5)	Emp. (6)	Plants (7)	Emp. (8)
Panel B: Second Stage								
ΔlogHHI (ind–local–year)$_{t-5\rightarrow t}$, IV	–0.047	–0.041	–0.047	–0.043	–0.061	–0.055	–0.040	–0.030
	–2.29	–2.36	–2.52	–2.97	–2.62	–2.67	–2.26	–2.02
Δlog(emp, ind–local–year)$_{t-5\rightarrow t}$	–0.012	–0.011	–0.014	–0.013	–0.014	–0.013	–0.012	–0.010
	–3.3	–3.56	–3.26	–3.89	–3.57	–3.76	–3.14	–3.08
Δlog(labor productivity)$_{t-5\rightarrow t}$	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
	12.31	12.42	10.91	11.05	12.15	12.27	10.83	10.98
Δlog(plants per segment)$_{t-5\rightarrow t}$	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002
	–2.11	–2.09	–1.87	–1.87	–2.15	–2.13	–1.87	–1.87

(*continued*)

Table 7 (*continued*)

	Dep. Var.: $\Delta\log(Avg.\ Wages)_{t-5\rightarrow t}$							
	SIC3							
	5% Market Share Threshold				10% Market Share Threshold			
	County		CZ		County		CZ	
M&A: (log *N* merged)	Plants (1)	Emp. (2)	Plants (3)	Emp. (4)	Plants (5)	Emp. (6)	Plants (7)	Emp. (8)
$\Delta\log(\text{plants per firm})_{t-5\rightarrow t}$	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	6.29	6.24	6.47	6.53	6.44	6.41	6.38	6.33
Industry–year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	468,000	468,000	468,000	468,000	468,000	468,000	468,000	468,000
R^2	0.0245	0.0256	0.0227	0.0237	0.0211	0.0228	0.0246	0.0266

Notes: This table examines the effects of employer concentration in a local labor market on wages using an instrumental variable (IV) approach. The instrument is the lagged (one to five years, $M\&A_{t-1}$ to $M\&A_{t-5}$) value of the log number of plants or employment involved in mergers of two firms in a given local labor market, defined by three-digit SIC codes and counties or CZs. We define a merger as an ownership change of a given plant between two firms that already had plants in the local labor market one year before the merger using the LBD. To ensure that the instruments for employment concentration are relevant, we require that the combined employment share of both the acquiring and target firms in the local labor market was at least 5 percent (Columns 1–4) or 10 percent (Columns 5–8) one year before a merger. Panel A presents estimates for the first-stage IV regression, in which the dependent variable is $\Delta\log\text{HHI (ind–local–year)}_{t-5\rightarrow t}$, the change in log(HHI) from five years before to the current year. Panel B presents estimates for the second-stage IV regression, in which the dependent variable is $\Delta\log(Avg.\ wages)_{t-5\rightarrow t}$, the change in average wages from five years before to the current year. All control variables in Panels A and B, such as $\Delta\log(labor\ productivity)_{t-5\rightarrow t}$, are also changes from five years before to the current year. The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousands to follow the U.S. Census Bureau's disclosure rules.

the current year, indicating that more recent M&As have a larger impact on changes in local-level employment concentration. The F-statistic for testing the relevance of the set of instruments is 53.79, well over the usual threshold value of ten (for example, Staiger and Stock 1997).

As can be seen in Columns 1–8 in Panel A, we continue to find that the coefficient estimates for the M&A activity instruments are positive and statistically significant at the 1 percent level, and F-statistics are greater than 40, whether (i) the local market is defined by counties or commuting zones, (ii) M&A activities are measured by the number of merged plants or employees therein, and (iii) we use 5 percent or 10 percent as a threshold value for the combined market share of the acquiring and target firms in the local labor market before mergers to define the instruments. The estimates in Panel A thus show that lagged M&A volumes are highly relevant and robust instruments for changes in local employment concentration.

Panel B of Table 7 displays results from estimating the second-stage regression in Equation 4 using the instrumented values of $\Delta \log \mathrm{HHI}_{jct-5 \to t}$. In Column 1, the coefficient on the instrumented change in log(HHI) is –0.047, significant at the 5 percent level. Thus, consistent with the hypothesis that labor market monopsony power detrimentally affects wages, the estimate shows that an increase in the degree of local-level employer concentration, driven by mergers of existing firms in the market, is associated with a reduction in average wages. Column 2, which uses the log number of employees affected by mergers as the instrument, shows a similar effect. The IV-based elasticity is –0.041, compared with baseline OLS elasticities of –0.009 to –0.010 in Table 2. The rest of the columns in the table report similar results using commuting zones to define the local labor markets (Columns 3 and 4) or using a 10 percent threshold for the combined employment share of both the acquiring and target firms in the local labor market (Columns 5–8). Using commuting zones to define local-level HHI, the reported elasticities imply that moving from one standard deviation below to one standard deviation above the mean-level HHI is associated with a reduction in wages between 9.1 percent and 14.4 percent.

D. Subsample Periods

We next investigate how the relation between wages and employer concentration evolves over the sample period. To this end, we divide the full sample for 1978–2016 into four subperiods and on each period rerun the wage regressions in Equation 1, which include the local-level HHI measure of employer concentration as the key independent variable (Table 8).[25] As shown in Panel A of Table 8, the coefficients on the HHI measure of employer concentration—defined at the three-digit SIC and county level—monotonically decline, becoming more negative over time, implying an increased elasticity of wages to local labor market concentration over the sample period. In the first subsample, covering 1978–1987, the coefficient on log(HHI) is zero. However, this coefficient declines to –0.009 in 1988–1997, –0.015 in 1998–2007, and in the final subsample of 2008–2016, the coefficient is –0.020. In the last column of the table, we

25. The four subperiods in Table 8 are: 1978–1987, 1988–1997, 1998–2007, and 2008–2016.

Table 8
Employer Concentration and Wages by Ten-Year Time Period

	Dep. Var.: Log Avg. Wages				
	1978–1987 (1)	1988–1997 (2)	1998–2007 (3)	2008–2016 (4)	2008–2010 (5)
Panel A: Counties as Local Areas					
log(HHI, SIC3–county–year)	0.000	–0.009	–0.015	–0.020	–0.020
	–0.11	–2.58	–4.30	–7.53	–6.26
log(emp, SIC3–county–year)	0.041	0.037	0.026	0.018	0.019
	30.66	28.21	19.45	15.12	12.06
log(labor productivity)	0.100	0.073	0.051	0.050	0.050
	40.21	32.52	27.18	27.26	21.12
log(plants per segment)	–0.002	–0.012	–0.010	–0.008	–0.008
	–1.45	–5.43	–5.11	–3.64	–2.65
log(plants per firm)	–0.002	–0.003	–0.006	0.000	–0.017
	–1.26	–1.55	–2.40	0.00	–2.05
Plant age (/100)	0.743	0.461	0.294	0.180	0.197
	18.66	22.66	24.19	20.37	16.71
Year fixed effects	Y	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y
Observations	248,000	250,000	238,000	209,000	69,000
R^2	0.6536	0.6181	0.5362	0.5785	0.6054

(*continued*)

Table 8 (*continued*)

	Dep. Var.: Log Avg. Wages				
	1978–1987 (1)	1988–1997 (2)	1998–2007 (3)	2008–2016 (4)	2008–2010 (5)
Panel B: Commuting Zones as Local Areas					
log(HHI, SIC3–CZ–year)	–0.001	–0.011	–0.014	–0.018	–0.018
	–0.48	–3.41	–3.48	–5.85	–5.46
log(employment, SIC3–CZ–year)	0.038	0.035	0.028	0.020	0.022
	31.11	23.31	20.09	14.22	12.62
log(labor productivity)	0.098	0.072	0.050	0.049	0.050
	33.67	28.16	24.29	25.58	20.89
log(plants per segment)	–0.002	–0.005	–0.007	0.000	–0.018
	–1.20	–2.12	–2.54	–0.10	–2.06
log(plants per firm)	–0.002	–0.011	–0.009	–0.008	–0.008
	–0.92	–5.11	–4.88	–3.71	–2.66
Plant age (/100)	0.815	0.490	0.306	0.186	0.204
	19.69	22.58	25.12	20.77	16.38
Year fixed effects	Y	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y
Observations	248,000	250,000	238,000	209,000	69,000
R^2	0.6515	0.6186	0.538	0.5804	0.6076

Notes: This table examines the basic effects of employer concentration in a local labor market on the wages of plants by ten-year period for 1978–2016. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(employment) are lagged by one year. The table presents estimates using three-digit SIC industries to compute HHI, log(employment), and log(plants per segment). Panels A and B present estimates using counties and CZs to compute HHI and log(employment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

estimate Equation 1 separately for the crisis period of 2008–2010 and find a similar magnitude of –0.020. In Panel B of Table 8, we use commuting zones rather than counties to compute local-level employer concentration. The results that are based on commuting zones exhibit a similar pattern to that found in Panel A—the sensitivity of wages to local labor market concentration increases over time. In 1978–1987, the coefficient on log(HHI) is –0.001 and insignificant. This coefficient declines to –0.011 in 1988–1997, –0.014 in 1998–2007, and to –0.018 in the final subsample of 2008–2016.

One potential explanation for the increasing sensitivity between wages and employer concentration over time is the decline in labor mobility over the sample period across both economic sectors and geographical areas (see, for example, Murphy and Topel 1987; Molloy, Smith, and Wozniak 2014). The effect of local labor market monopsony hinges to a large extent on limits to labor mobility across markets (for a review, see Boal and Ransom 1997). Thus, to the extent that workers have become less mobile in the United States over the past decades, employer concentration at the local level is more likely to restrict workers' employment choice-set, explaining a rising sensitivity between wages and employer concentration over the sample period. An additional mechanism potentially explaining the rise in the sensitivity of wages to employer concentration is the secular decline in employee bargaining power stemming from the decline in unionization rates beginning in the 1970s (see, for example, Card 1992). We turn to this mechanism next.[26]

E. Employer Concentration, Unions, and Wages

While employer concentration may enable firms to pay lower wages, unionization strengthens labor's bargaining position and may enable employees to diminish employers' monopsony power. We next empirically test whether unionization mitigates the ability of firms to reduce wages in concentrated markets. To do so, we interact our local measure of employer concentration with the degree of unionization at the industry level, employing the following regression specification:

$$(5)\quad \log(avg.\ wages)_{pfjt} = \beta_0 + \beta_1 \log(\text{HHI})_{jct-1} + \beta_2 \log(\text{HHI})_{jct-1} \times Union_{jt-1} + \beta_3 Union_{jt-1} + \beta_4 \mathbf{X}_{pfjt} + \beta_5 \mathbf{Z}_{jct-1} + \boldsymbol{\delta}_{jt} + \boldsymbol{\mu}_{ft} + \varepsilon_{pfjt},$$

where $Union_{jt-1}$ is the one-year lagged union coverage rate for industry j associated with plant i, and all other variables as defined in Equation 1. Union coverage rates are from the CPS ORG data as explained in Section II.A.3. The main coefficient of interest in this regression is β_2, which measures the degree to which unionization rates affect the sensitivity of wages to employer concentration.

26. Lipsius (2018) finds that the link between wages and HHI has weakened over time. There are two main differences between the analysis in Lipsius (2018) and ours. First, we focus on manufacturing firms, which enable us to include a control for productivity, while he studies all industries. Second, we conduct our regression analysis at the establishment level, exploiting establishment level controls, while he aggregates establishment–years from the LBD to the local labor market level. Rerunning our establishment-level regressions using all industries in the LBD confirms our results that the relation between HHI and wages increases in absolute value over time, albeit more so in manufacturing than when analyzing all industries in the LBD.

Table 9 presents estimates of Equation 5 using plant-level data for 1978–2016.[27] Column 1 of Panel A shows that, as in Table 2, controlling for year, industry, and firm fixed effects and employing plant-level and county–industry-level controls, average workers' wages at manufacturing plants are lower when the local labor market (defined at the county level) is more concentrated in a given three-digit SIC industry. Importantly, the coefficient on the interaction term between local employer concentration and the union coverage rate is positive. Consistent with the hypothesis, the negative relation between employer concentration and wages is thus mitigated among plants that operate in industries with higher unionization rates. Based on the estimates, in industries with unionization rates near zero, the elasticity between wages and local-level HHI is approximately −0.016, while in contrast, at the average unionization rate (19.8 percent), the elasticity between wages and local-level labor market concentration wages declines by between 29 percent and 44 percent, depending on the specification. For example, the regression estimates in Column 1 imply that at a zero unionization rate the elasticity of wages to employer concentration is −0.017, while for industries at the mean unionization rate the elasticity is approximately −0.010. Based on these elasticities, in industries with near zero unionization, moving from one standard deviation below to one standard deviation above the mean level of HHI is associated with a 2.7 percent reduction in wages, while for firms at the average level of unionization the same HHI movement reduces wages by only 1.6 percent.

Column 2 includes industry-by-year and firm-by-year fixed effects and exhibits results consistent with those in Column 1—the negative relation between employer concentration and wages is mitigated by high unionization rates at the industry level. In terms of economic magnitude, estimates in Column 2 indicate that a one standard deviation increase in unionization rates from their average reduces the elasticity of wages to HHI by approximately half, from −0.009 to −0.005. In Columns 3 and 4 we repeat the analysis of the first two columns using HHI measures that are calculated at the county and four-digit industry levels and find similar results. In the last four columns of Table 9 we repeat the analysis in Columns 1–4 using commuting zones to define local labor markets. The results based on commuting zones are similar to those found using counties, with labor unions reducing the elasticity of wages to employer concentration. The results are thus consistent with unions providing bargaining power to workers in wage negotiations, mitigating a negative effect of local labor market concentration on wages.

F. Employer Concentration and Rent Sharing

The analysis thus far has focused on the relation between employer concentration and wages in local labor markets. In addition to wage levels, concentration of employers may also affect the transmission of productivity growth into wage changes. Standard economic theory would suggest that in competitive or near-competitive labor markets increases in labor productivity should translate into increased wages, with workers paid

27. As explained in Section II.A, data on industry-level union coverage rates are available from 1983 only. Thus, we impute unionization coverage rates before 1983 (that is, 1978–1982) using values for corresponding industries in 1983.

Table 9
Local Employer Concentration, Unions, and Wages

	Dep. Var.: Log Avg. Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
log(HHI, SIC3–county–year)	–0.017	–0.014	–0.017	–0.015	–0.017	–0.015	–0.016	–0.017
	–4.51	–3.94	–4.51	–4.30	–4.18	–3.63	–4.44	–4.02
log(emp, ind–local–year)	0.033	0.032	0.030	0.031	0.033	0.032	0.031	0.031
	36.55	33.67	41.99	40.57	33.42	30.63	35.95	33.52
log(labor productivity)	0.072	0.069	0.067	0.064	0.071	0.068	0.067	0.063
	47.92	46.39	46.26	41.98	39.92	34.27	35.09	30.48
Union	0.186	0.221	0.154		0.205	0.268	0.162	
	14.13	3.89	12.35		12.00	4.22	10.91	
log HHI × Union	0.036	0.028	0.022	0.022	0.038	0.031	0.024	0.028
	4.19	3.00	2.38	2.35	4.06	3.09	2.70	2.68
log(plants per segment)	–0.007	–0.008	–0.005	–0.007	–0.006	–0.007	–0.005	–0.006
	–5.15	–5.88	–4.82	–4.75	–4.38	–4.76	–4.25	–4.06

(*continued*)

Table 9 (*continued*)

	Dep. Var.: Log Avg. Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
log(plants per firm)	–0.007		–0.006		–0.008		–0.007	
	–4.53		–4.43		–4.64		–4.44	
Plant age (/100)	0.267	0.275	0.257	0.264	0.286	0.293	0.275	0.281
	30.65	33.28	32.47	31.78	30.42	31.58	28.70	28.75
Year fixed effects	Y		Y		Y		Y	
Industry fixed effects	Y		Y		Y		Y	
Industry–year fixed effects		Y		Y		Y		Y
Firm fixed effects	Y		Y		Y		Y	
Firm–year fixed effects		Y		Y		Y		Y
Observations	946,000	946,000	946,000	946,000	946,000	946,000	946,000	946,000
R^2	0.5714	0.6550	0.5849	0.6728	0.5720	0.6557	0.5862	0.6741

Notes: This table examines the interactive effects of employer concentration in a local labor market and industry union coverage rates on the wages of plants. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI), log(employment), and Union are lagged by one year. Columns 1–4 (Columns 5–8) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute HHI, log(employment), and log(plants per segment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

their marginal product. Empirical evidence has provided general support for a link between productivity and wage growth (see, for example, Stansbury and Summers 2017), although this link appears to have declined since the early 1980s (see, for example, Mishel 2012; Bivens and Mishel 2015). Following these results, we hypothesize that labor market employer concentration impedes the translation of productivity growth to wage increases, as employers use their monopsony power to avoid wage hikes, thereby capturing rents from increased productivity.

Before analyzing empirically how the relation between wages and productivity varies based on the degree of employer concentration, it is useful to consider the theoretical underpinnings of this relation. To fix ideas, we provide a short theoretical analysis within a classic monopsony and Cournot-oligopsony framework. Clearly, alternative frameworks exist modeling monopsonistic labor market competition—for example, search-based models—and in these, the conditions governing the relation between productivity and wages may be quite different than those derived here. As such, the empirical results in this section should be viewed as placing additional discipline on the various theoretical frameworks employed in the monopsony literature.

Beginning with the case of a monopsonist facing a constant marginal product of labor A, and assuming a labor supply function $L(w)$, the well-known first order condition is:

$$(6) \quad A = w^* \left[1 + \frac{1}{\varepsilon^L(w^*)}\right],$$

with $\varepsilon^L(w)$ the elasticity of labor supply and w^* the optimal monopsonist-set real wage. We show in Appendix 2 that this first-order condition implies that if labor supply elasticity is decreasing in wage—that is, $d\varepsilon^L/dw < 0$—then the elasticity of the wage with respect to productivity is smaller than unity. That is, when labor supply elasticity is declining with wages—an empirically reasonable assumption—the elasticity of wages to productivity is smaller in the monopsonist case than in the case of a perfectly competitive labor market.[28]

This result is intuitive. From Equation 6, the monopsonist pays a fraction (less than one) of productivity, but when the elasticity of labor supply is decreasing in wages, this fraction declines as productivity rises. The elasticity of wages to productivity is thus smaller than unity. (Alternatively, rearranging Equation 6 in the classic manner as $(A - w^*)/w^* = 1/\varepsilon^L(w^*)$, with the left-hand side of the equation being the well-known "rate of exploitation," we see that a declining labor supply elasticity implies that the rate of exploitation increases in the productivity level A.)

Turning to a Cournot-oligopsony setting, consider N firms competing for labor: firm i chooses to employ labor l_i while facing the wage function $w(L)$, with $L = \sum_k l_k$. In a symmetric Nash Equilibrium, the equilibrium wage w^* satisfies:

$$(7) \quad A = w^* \left[1 + \frac{1}{N\varepsilon^L(w^*)}\right],$$

28. Indeed, a declining elasticity of labor supply with respect to wages is implicit in the (generally stronger) assumption of backward bending labor supply curves discussed in the labor economics literature (see for example, Keane 2011).

with $\varepsilon^L(w)$ the elasticity of the labor supply function $L(w)$, equal to the inverse of the wage function $w(L)$, defined above.[29]

Based on Equation 7, we show in the appendix that when $d\varepsilon^L/dw < 0$, as the number of competing firms increases, the elasticity of the equilibrium wage to productivity converges from below to unity:

$$(8) \quad \lim_{N\to\infty} \varepsilon_N^{w^*}(A) = 1 \text{ and } \varepsilon_N^{w^*}(A) < 1,$$

with $\varepsilon_N^{w^*}(A)$ the elasticity of the equilibrium wage to productivity when N firms compete in the labor market. Thus, with declining labor elasticity, as the number of competing firms rises, the pass-through of productivity to wages rises from the monopsonist-level elasticity—which, as shown above, is less than one—to the perfectly competitive elasticity (which equals one). This convergence need not be monotonic in the number of competing firms, N, but by definition of convergence, for any level of elasticity $\varepsilon^* < 1$, there exists a threshold number of firms N^*, such that if the number of firms competing in the labor market is above N^*, the elasticity of wages to productivity is above ε^*.

In sum, within a Cournot-oligopsony framework, a key condition for the pass-through of productivity to wages to exhibit an increasing trend with the level of competition, is that the elasticity of labor supply declines with wages. Clearly, conditions governing the relation between labor market competition and productivity-to-wage pass-through rates may be quite different within alternative modeling frameworks of nonperfectly competitive labor markets. As stated above, we view the empirical results in this section on the relation between labor market concentration and productivity-to-wages pass-through rates as placing discipline on these theoretical frameworks.

To empirically test whether the sensitivity of wage growth to productivity growth is affected by local-level employer concentration, we use the following first-differences interaction specification:

$$(9) \quad \Delta\log(\mathit{avg.\ wages})_{pfjt} = \beta_0 + \beta_1\log(\mathrm{HHI})_{jct-1} + \beta_2\Delta\log(\mathit{labor\ productivity})_{pfjt} + \beta_3\log(\mathrm{HHI})_{jct-1} \times \Delta\log(\mathit{labor\ productivity})_{pfjt} + \beta_4\mathbf{X}_{pfjt} + \beta_5\mathbf{Z}_{jct-1} + \boldsymbol{\delta}_{jt} + \boldsymbol{\mu}_{ft} + \varepsilon_{pfjt},$$

where $\Delta\log(\mathit{avg.\ wages})_{pfjt}$ is the log change in average plant wages for production workers and $\Delta\log(\mathit{labor\ productivity})_{pfjt}$ is the log change in labor productivity in plant p, industry j, county c, and year t. All control variables are defined as in Equation 1, while $\boldsymbol{\delta}_{jt}$ is a vector of industry-by-year fixed effects, and $\boldsymbol{\mu}_{ft}$ is a vector of firm-by-year fixed effects. We focus on production workers in this specification since their compensation is potentially more sensitive to productivity due to rent sharing (for example, Freeman and Medoff 1981).

Table 10 reports estimation results. Across columns in Table 10, the coefficient on $\Delta\log(\mathit{labor\ productivity})$ is positive and significant at the 1 percent level, confirming a positive association between wage growth and productivity growth at the plant level (see, for example, Stansbury and Summers 2017). Importantly, consistent with our

29. For technical reasons, to maintain a well-defined game we assume here that the elasticity of labor supply with respect to wages is bounded away from zero. This requirement can be relaxed at the cost of additional expositional complexity.

Table 10
Employer Concentration and Sensitivities of Wage Changes to Productivity Changes

	Dep. Var.: Δlog Avg. Production Worker Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
log(HHI, ind–local–year)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	3.85	4.22	3.96	4.75	4.16	4.82	3.87	5.09
Δlog(labor productivity)	0.114	0.109	0.115	0.110	0.109	0.105	0.110	0.106
	56.39	52.45	60.16	55.89	45.32	42.49	47.50	45.80
log(HHI) × Δlog(labor productivity)	–0.009	–0.009	–0.011	–0.012	–0.008	–0.008	–0.011	–0.011
	–4.69	–4.77	–4.18	–4.17	–5.24	–5.25	–4.76	–4.84
log(plants per segment)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.06	–0.19	0.96	0.51	0.03	–0.24	0.98	0.51
log(plants per firm)	0.000		0.000		0.000		0.000	
	–0.31		–0.70		–0.27		–0.59	
Plant age (/100)	–0.007	–0.008	–0.007	–0.008	–0.007	–0.008	–0.007	–0.008
	–3.11	–3.44	–3.14	–3.32	–2.68	–3.10	–2.72	–3.01

(*continued*)

Table 10 (*continued*)

	Dep. Var.: Δlog Avg. Production Worker Wages							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
Year fixed effects	Y		Y		Y		Y	
Industry fixed effects	Y		Y		Y		Y	
Industry–year fixed effects		Y		Y		Y		Y
Firm fixed effects	Y		Y		Y		Y	
Firm–year fixed effects		Y		Y		Y		Y
Observations	946,000	946,000	946,000	946,000	946,000	946,000	946,000	946,000
R^2	0.0877	0.2971	0.0880	0.3087	0.0877	0.2971	0.0881	0.3088

Notes: This table examines how employer concentration shapes sensitivities of changes in production worker wages to changes in labor productivity. The dependent variable is the log change in average wages per production worker as defined in Table 1. log(HHI) is lagged by one year. Columns 1–4 (Columns 5–8) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute HHI, log (employment), and log(plants per segment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

prediction regarding the role of monopsony power in labor markets, the coefficient on the interaction term log(HHI) × Δlog(*labor productivity*) is negative and significant at the 1 percent level. Estimates in Column 2, which controls for both industry-by-year and firm-by-year fixed effects, imply that a one standard deviation decrease in HHI from its mean increases the elasticity of production worker wages to productivity by approximately 8.5 percent, from 0.115 to 0.125. Alternatively, estimates in Columns 4–8, which employ the commuting zone classification to define local-level employer concentration, imply that a one standard deviation decrease in HHI from its mean, increases the elasticity of production worker wages to productivity by between 11.2 percent and 18 percent. Consistent with our prediction, therefore, when labor markets are more competitive, productivity increases are associated with larger increases in wages, as employers compete for workers. In contrast, higher levels of employer concentration impede the translation of productivity growth into wage growth.

G. Wages, Market Concentration, and the China Shock

A growing body of literature investigates the impact of increased trade with China—the "China shock"—on labor markets in the United States. For example, Autor, Dorn, and Hanson (2013) and Autor et al. (2014) find that local labor markets more exposed to import penetration from China exhibit higher unemployment, lower labor-force participation, and reduced wages. In this subsection, we add to the literature on the China shock and the labor market effects of increased globalization by investigating the effect of import penetration from China on local labor market concentration. We hypothesize that by causing employers to shut down a fraction of their operations, increased import competition from China may have led to an increase in local labor market concentration. Thus, we argue that in addition to labor displacement and an associated decline in wages due to reduced labor demand, increased import competition from China may have an additional effect of reducing wages of *nondisplaced* workers due to an increase in employer concentration.

We construct an industry-by-year measure of import exposure per worker from China to the United States equal to the industry-level dollar value of imports scaled by total employment in the industry in a given year.[30] Specifically, we define import exposure from China as: $\textit{China Exposure}_{j,t} = \dfrac{\textit{Imports from China}_{j,t}}{\sum_{i=1}^{N} \textit{Employment}_{i,j,t}}$, in which $\textit{Imports from China}_{j,t}$ represents the dollar value of imports from China to the United States in industry j and year t, and $\textit{Employment}_{i,j,t}$ represents employment in plant i operating in industry j and year t. We limit our analysis to plant–years in 1992–2008, given that China import penetration data are available for 1991–2007 and that we use lagged China exposure as an independent variable.

We first adjust our main empirical specification in Equation 1 by including *China Exposure* as an additional control. Table 11 presents the results and shows that the coefficient on *China Exposure*, measured at the three-digit SIC level, is negative and significant at the 1 percent level, consistent with existing research documenting negative

30. See for example, Autor, Dorn, and Hanson (2013). The data sources for the import and total employment data are U.N. Comtrade and the LBD, respectively. We thank David Dorn for making the import data available on his website.

Table 11
China Import Penetration, Local Employer Concentration, and Wages

	Dep. Var.: Log Avg. Wages			
	County		CZ	
	SIC3 (1)	SIC4 (2)	SIC3 (3)	SIC4 (4)
log(HHI, ind–local–year)	–0.009	–0.015	–0.004	–0.008
	–3.02	–5.32	–1.25	–2.99
China exposure (ind–year)	0.000	–0.001	0.000	–0.001
	–2.99	–7.06	–2.37	–6.90
log(emp, ind–local–year)	0.026	0.023	0.027	0.024
	17.36	16.84	14.51	13.40
log(labor productivity)	0.078	0.078	0.078	0.078
	38.34	38.00	32.81	32.74
log(plants per segment)	–0.020	–0.016	–0.020	–0.017
	–11.00	–9.01	–9.76	–8.14
log(plants per firm)	–0.004	–0.007	–0.005	–0.007
	–1.85	–3.41	–1.88	–3.04
Plant age (/100)	0.341	0.337	0.357	0.352
	26.74	26.21	27.09	25.82
Year fixed effects	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Observations	350,000	350,000	350,000	350,000
R^2	0.5349	0.5327	0.5345	0.5330

Notes: This table examines the effects of employer concentration in a local labor market on wages controlling for the effect of import penetration from China on wages. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(employment) are lagged by one year. China exposure is defined as total value of import from China to the U.S. scaled by total employment at the industry by year level. Columns 1 and 2 (Columns 3 and 4) present estimates using counties (CZs) to define local labor markets. Columns 1 and 3 (Columns 2 and 4) present estimates using three- (four-) digit SIC industries to compute HHI, log(employment), and log(plants per segment). The t-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousands to follow the U.S. Census Bureau's disclosure rules.

consequences of the China shock on labor market outcomes. In terms of economic magnitude, a one standard deviation increase in China exposure is associated with a 0.41 percent ($=-0.475\times 0.009$) reduction in average wages. Importantly, however, including this direct control for the China exposure does not significantly affect our estimates for local-level employer concentration, with the coefficient on HHI remaining negative and significant at the 1 percent level. Column 2, which uses four-digit SIC codes and

Table 12
The Exposure to Chinese Imports and Local Employer Concentration

	Dep. Var.: Log(HHI, ind–local–year)			
	County		CZ	
	SIC3 (1)	SIC4 (2)	SIC3 (3)	SIC4 (4)
China exposure (ind–year)	0.004	0.002	0.004	0.002
	6.18	3.88	3.98	2.17
log(emp, ind–local–year)	–0.431	–0.326	–0.522	–0.435
	–13.49	–11.65	–15.81	–14.68
log(labor productivity)	–0.005	–0.004	0.012	0.007
	–0.82	–0.62	1.51	1.00
log(plants per segment)	0.033	0.009	0.056	0.027
	4.93	1.61	5.54	2.54
log(plants per firm)	–0.044	–0.027	–0.053	–0.035
	–6.12	–4.26	–6.56	–4.67
Plant age (/100)	0.929	0.939	0.781	0.950
	19.17	20.13	12.06	20.46
Year fixed effects	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Observations	350,000	350,000	350,000	350,000
R^2	0.6160	0.5557	0.6684	0.6294

Notes: This table examines how exposure to China import penetration affects local-level employer concentration. The table uses three-digit SIC industries to compute HHI, China exposure, log(employment), and log(plants per segment). The dependent variable is log(HHI) as defined in Table 1. t-statistics based on standard errors adjusted for sample clustering at the county level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

counties, and Columns 3 and 4, which use commuting zones, show a similar result. Controlling for the China shock does not much alter the baseline relation between employer concentration and wages.

We next turn to analyzing the effect of the China shock on labor market concentration. Given the disruptions to the manufacturing sector documented in Autor et al. (2013, 2014), we hypothesize that increased exposure to competition from China should increase local-level employer concentration. As such, we are interested herein in a *determinant* of labor market concentration, in contrast to the results in prior sections dealing with the effects of such concentration.

To analyze how the China shock relates to employer concentration, we run the following specification, regressing the local-level HHI employer concentration measure on our measure of exposure to competition from China:

$$\log(\text{HHI})_{jct} = \beta_0 + \beta_1 \textit{China Exposure}_{jt} + \beta_2 \mathbf{X}_{pfjt} + \beta_3 \mathbf{Z}_{jct-1} + \boldsymbol{\delta}_{jt} + \boldsymbol{\mu}_{ft} + \varepsilon_{pfjt}, \tag{10}$$

$\log(\text{HHI}_{jct})$ is log local-level employer concentration in county or commuting zone c and industry j measured at either the three- or four-digit SIC level; $\textit{China Exposure}_{jt}$ is defined as the total value of imports from China to the United States scaled by total employment for industry j in year t; and all other variables are defined as in Equation 1.

Table 12 presents the results of estimating Equation 10. Across the columns, we find that the coefficient on exposure to Chinese imports is significantly positive at the 1 percent to 5 percent level, suggesting that industry-level import competition is indeed associated with increased concentration of employers in the local labor market. In terms of economic magnitude, estimates in Column 3, which uses three-digit SIC codes and commuting zones, suggest that a one standard deviation increase in Chinese import competition leads to a 0.035 (=3.980 × 0.009) point increase in log(HHI).

After confirming our hypothesis that increased import competition from China is associated with higher local employer concentration, it is natural to hypothesize that such exposure to Chinese imports will have an indirect effect on wages through increased local-level labor market concentration. According to this, increased exposure to import competition from China increases employer concentration, thereby reducing wages. However, given that exposure to China affects wages directly (as shown in Autor et al. 2013, 2014), using import penetration from China as an instrument for employer concentration does not meet the exclusion restriction. Hence, it is empirically challenging to disentangle the indirect effect from the direct effect of exposure to Chinese import competition on wages.

IV. Conclusion

We use manufacturing plant-level data from the U.S. Census Bureau for 1978–2016 to provide evidence that wages are lower in local labor markets in which employers are more concentrated. We provide evidence relating local-level employer concentration to wages along a host of margins. Exploiting merger activity as an instrument for local-level concentration in labor markets, we show that wages decline following increases in local-level employer concentration. Further, the negative relation between employer concentration and wages increases over time and is particularly strong when labor unionization rates are low. Thus, in the presence of concentrated labor markets, unionization may mitigate monopsony power in labor markets by increasing workers' bargaining positions in wage determination processes. In addition, we show that higher employer concentration impairs the transmission of productivity growth into wage increases. As such, the results suggest that weak bargaining power reduces the ability of workers to benefit from productivity growth. Finally, we analyze one particular determinant of local labor market concentration, showing that increased exposure to competition from China led to higher concentration of employers. Taken as a whole, the results underscore the importance of analyzing market power within labor markets and relative employer–employee bargaining positions as important determinants of wage-setting behavior.

Appendix 1

Table A1
Contemporaneous Local Employer Concentration and Wages

	Dep. Var.: Log(Avg. Wages)							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
log(HHI, ind–local–year), [*t*]	–0.012	–0.011	–0.014	–0.013	–0.011	–0.011	–0.013	–0.013
	–3.57	–3.69	–4.50	–4.65	–3.50	–3.59	–4.26	–4.20
log(emp, ind–local–year), [*t*]	0.032	0.031	0.030	0.030	0.032	0.031	0.030	0.030
	34.83	32.36	36.82	35.16	31.72	29.03	32.61	30.19
log(labor productivity)	0.073	0.070	0.068	0.064	0.072	0.069	0.067	0.064
	48.46	41.61	43.24	36.74	40.56	34.84	35.83	30.92
log(plants per segment)	–0.007	–0.008	–0.006	–0.007	–0.006	–0.007	–0.006	–0.006
	–5.14	–5.33	–4.88	–4.73	–4.43	–4.59	–4.51	–4.07
log(plants per firm)	–0.007		–0.006		–0.008		–0.007	
	–4.63		–4.57		–4.66		–4.54	
plant age (/100)	0.280	0.290	0.271	0.280	0.298	0.307	0.287	0.296
	31.32	32.03	30.93	30.84	31.17	32.46	29.61	29.68

(*continued*)

Table A1 (*continued*)

	Dep. Var.: Log(Avg. Wages)							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
Year fixed effects	Y		Y		Y		Y	
Industry fixed effects	Y		Y		Y		Y	
Industry–year fixed effects		Y		Y		Y		Y
Firm fixed effects	Y		Y		Y		Y	
Firm–year fixed effects		Y		Y		Y		Y
Observations	941,000	941,000	941,000	941,000	941,000	941,000	941,000	941,000
R^2	0.5735	0.6554	0.5871	0.6733	0.5742	0.6562	0.5884	0.6746

Notes: This table examines the effects of contemporaneous employer concentration in a local labor market on the wages of plants. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(emp) are contemporaneous with the log of average wages per worker. Columns 1–4 (Columns 5–8) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute HHI, log(employment), and log(plants per segment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

Table A2

Local Employer Concentration and Wages without Plant-Level Controls

	Dep. Var.: Log(Avg. Wages)							
	County				CZ			
	SIC3 (1)	SIC3 (2)	SIC4 (3)	SIC4 (4)	SIC3 (5)	SIC3 (6)	SIC4 (7)	SIC4 (8)
log (HHI, ind–local–year)	–0.009	–0.008	–0.012	–0.010	–0.009	–0.008	–0.011	–0.010
	–2.85	–2.69	–3.78	–3.53	–2.76	–2.56	–3.40	–3.06
log(emp, ind–local–year)	0.034	0.034	0.032	0.033	0.034	0.034	0.032	0.034
	37.42	35.41	41.36	40.40	33.69	31.11	36.04	34.08
Year fixed effects	Y		Y		Y		Y	
Industry fixed effects	Y		Y		Y		Y	
Industry–year fixed effects		Y		Y		Y		Y
Firm fixed effects	Y		Y		Y		Y	
Firm–year fixed effects		Y		Y		Y		Y
Observations	946,000	946,000	946,000	946,000	946,000	946,000	946,000	946,000
R^2	0.5539	0.6418	0.5702	0.6622	0.5542	0.6423	0.5714	0.6633

Notes: This table examines the effects of employer concentration in a local labor market on the wages of plants, without controlling for plant-level covariates. The dependent variable is the log of average wages per worker as defined in Table 1. log(HHI) and log(emp) are lagged by one year. Columns 1–4 (Columns 5–8) present estimates using counties (CZs) to define local labor markets. Columns 1–2 and 5–6 (Columns 3–4 and 7–8) present estimates using three- and four-digit SIC industries to compute HHI, log (employment), and log(plants per segment). The *t*-statistics based on standard errors adjusted for sample clustering at the county or CZ level are reported below the coefficient estimates. The numbers of observations are rounded to the nearest thousand to follow the U.S. Census Bureau's disclosure rules.

Appendix 2

Proof:

Consider first a monopsonist facing a constant marginal product of labor A and a labor supply function $L(w)$ with a positive elasticity of labor supply. The well-known wage-setting first-order condition is:

$$\text{(A1)}\quad A = w^* \left[1 + \frac{1}{\varepsilon^L(w^*)}\right],$$

with $\varepsilon^L(w)$ the elasticity of labor supply and w^* the optimal real wage. Treating Equation A1 as defining an implicit function between A and w^*, the elasticity of A with respect to w^*, $\varepsilon^A(w^*)$, can be calculated to be:

$$\text{(A2)}\quad \varepsilon^A(w^*) = 1 - \frac{d\varepsilon^L(w^*)}{dw} \times \frac{w^*}{\varepsilon^L(w^*)[1+\varepsilon^L(w^*)]}.$$

From Equation A2 we have that $\varepsilon^A(w^*) > 1$ when the elasticity of labor supply is declining with wage – that is, when $d\varepsilon^L/dw < 0$. Denoting $\varepsilon^{w^*}(A)$ to be the elasticity of w^* with respect to A, and noting that this elasticity is the reciprocal of the elasticity of A with respect to w^*, we have that $\varepsilon^{w^*}(A) < 1$ when $d\varepsilon^L/dw < 0$. That is, when labor supply elasticity is declining with wages the elasticity of wages to productivity is smaller in the monopsonist case than in the case of a perfectly competitive labor market.

Turning to a Cournot-oligopsony setting, consider N firms competing for labor: firm i chooses to employ labor l_i while facing the wage function $w(L)$, with $L = \sum_k l_k$. Denote the labor supply curve—that is, the inverse of the wage function $w(L)$ – as $L(w)$. To maintain a well-defined game and for expositional simplicity assume that the elasticity of labor supply with respect to the wage is bounded away from zero. It is easy to show then that in a symmetric Nash Equilibrium, the equilibrium wage w^* satisfies:

$$\text{(A3)}\quad A = w^* \left[1 + \frac{1}{N\varepsilon^L(w^*)}\right],$$

with $\varepsilon^L(w)$ the elasticity of labor supply function. As above, treating Equation A3 as defining an implicit function between A and the optimal wage w^*, the elasticity of A with respect to w^* when N firms compete in the market can be calculated to be:

$$\text{(A4)}\quad \varepsilon_N^A(w^*) = 1 - \frac{d\varepsilon^L(w^*)}{dw} \times \frac{w^*}{\varepsilon^L(w^*)[1+N\varepsilon^L(w^*)]}.$$

Defining $\varepsilon_N^{w^*}(A)$ to be the elasticity of w^* with respect to A (with N competing firms), by an analogous argument to the monopsonist case above, we have that if $d\varepsilon^L/dw$ is negative, then $\varepsilon_N^{w^*}(A) < 1$ for all N. To show that $\lim_{N\to\infty} \varepsilon_N^{w^*}(A) = 1$. Note first that Equation A3 and the assumption that the elasticity is bounded away from zero implies that $\lim_{N\to\infty} w^*(N) = A$, with $w^*(N)$ the wage under the symmetric Nash Equilibrium with N firms. The result that $\lim_{N\to\infty} \varepsilon_N^{w^*}(A) = 1$ stems then directly from Equation A4, the assumption that the elasticity of labor supply is bounded away from zero, and the fact that $\lim_{N\to\infty} w^*(N) = A$.

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