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Common ownership in labor markets

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Common Ownership in Labor Markets

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ABSTRACT

In this paper, we study the effects of common ownership, the extent to which firms are linked via common owners, on employee earnings in U.S. local labor markets. Between 1999 and 2017, common ownership in local labor markets has more than doubled. Panel regressions show that employee earnings in a local labor market are negatively associated with common ownership. To identify causal effects, we use a firm's addition to the S&P 500 index as a shock to common ownership of its competitors in a local labor market. Using a matched difference-in-differences analysis, we find that, after a firm enters the S&P 500 index, the average annual earnings per employee of its local competitors decreases relative to the counterfactual. The effect of index inclusion shocks on employee earnings is stronger in local labor markets where the shares of S&P 500 incumbents are higher before a shock.

JEL Classification Codes: J42, J31, L40, D40, G34

Key Words: Monopsony, oligopsony, labor markets, competition policy, common ownership

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1 Introduction

Ownership of U.S. publicly traded corporations by institutional investors went from less than 10 percent in the 1950s to 67 percent by 2010 (Blume and Keim, 2012). Together with the shift in assets from actively managed funds to passively managed index funds, this substantially drove up common ownership of publicly traded firms, the extent to which different firms share common owners (see, for example, Azar and Vives, 2021; Backus, Conlon and Sinkinson, 2021b).¹ This trend has raised the alarm that a small number of giant asset managers (for example, BlackRock, Vanguard, and State Street) could effectively control most large, publicly traded firms in the near future (Coates, 2018). Increased common ownership could increase firms' employer market power, which in turn could contribute to the wage stagnation since the 1970s (Goshen and Levit, 2021; Steinbaum, 2021; Azar and Vives, 2021).² Although this argument is theoretically appealing, little is known about whether and how common ownership affects employee earnings in reality.

This paper provides the first empirical evidence on the effects of common ownership on employee earnings in the U.S. economy. We define a local labor market as the interaction between a commuting zone (CZ) and an industry, as in Rinz (2020). To measure common ownership in a local labor market, we combine data on institutional ownership of publicly traded firms from Backus, Conlon and Sinkinson (2021b) with data on firms' employment shares in each local labor market, constructed from establishment-level employment data from Data Axle. To measure common ownership in a local labor market, we use information on both publicly traded and privately held firms. We find that standard measures of common ownership more than doubled on average in local labor markets in the United States between 1999 and 2017. To measure employee earnings at the local labor market level, we used data in the Quarterly Census of Employment and Wages (QCEW).

To identify the effect of common ownership on employee earnings, we use the strategy of Boller and Scott Morton (2020), based on natural experiments generated by the addition of some public firms to the S&P 500 index. The key idea is that a firm entering the S&P 500 index (which we refer to as a *focal firm*) experiences a sharp increase in institutional ownership from index funds. This, in turn, increases overlap between its ownership and that of its publicly traded industry competitors (*nonfocal firms*), especially S&P 500 incumbents. This results in higher common ownership for the nonfocal firms. Because each local labor market

¹For earlier contributions that documented the secular rise of common ownership, see also Azar (2012); Fichtner, Heemskerk and Garcia-Bernardo (2017); Azar (2017, 2020).

²See Bivens and Mishel (2015) for a paper that documents the stagnation of wages relative to productivity in recent decades.

has different firm employment shares before the same S&P 500 index addition event, the same event generates heterogeneous increases in common ownership with local competitors across commuting zones. Based on this variation, we use a difference-in-differences (DiD) design to estimate the causal effect of common ownership on employee earnings.

In DiD regressions, we compare changes in employee earnings at nonfocal firms in local labor markets where at least one firm enters the S&P 500 index (treated local labor markets) to changes in matched local labor markets where no firms ever enter the S&P 500 index within the estimation window (control local labor markets).³ The main identification assumption underlying the DiD design is that the employee earnings of nonfocal firms in treated local labor markets would have evolved similarly to earnings in control local labor markets in the absence of S&P 500 index addition events.

As expected, S&P 500 index additions indeed lead to an increase in the average common ownership of nonfocal firms in treated local labor markets. Specifically, our estimate shows that, compared to control local labor markets, the average common ownership of nonfocal firms in treated local labor markets increases 0.3 percentage points during the five-year window after treatment. The magnitude of the estimated effect is economically meaningful and represents a 12.5 percent increase relative to the sample mean of 2.4 percentage points in treated local labor markets one year prior to treatment.

S&P 500 index additions lead to lower average employee earnings of nonfocal firms in treated local labor markets. The average annual earnings per employee among nonfocal firms in treated local labor markets are 1.1 percent lower compared to those in control local labor markets during the posttreatment period. Given that the average employee earnings among nonfocal firms in treated local labor markets are \$44,317 one year prior to treatment, our estimates suggest that an employee of nonfocal firms in treated local labor markets with average pay earns \$2,437 less relative to the counterfactual during the first five years after treatment. The results are robust to alternative sets of matched control local labor markets, using an alternative source of institutional ownership data, and using different local labor market definitions. Additional analyses also suggests that the estimated effect on employee earnings comes from labor markets with low union coverage rates, and is not driven by changes in workforce characteristics.

The estimated effect of common ownership on employee earnings varies with the share of S&P 500 incumbent firms in a treated local labor market during the year of an index addition event. We split the treated local labor markets into terciles based on the share of S&P 500 incumbent firms and reestimate DiD regressions for each subsample. The estimated effect of

³Local labor markets where employing firms exit the S&P 500 are excluded from the treatment and control groups.

index-addition events are the largest for treated local labor markets in the top tercile of S&P 500 share. Annual earnings per employee among nonfocal firms in treated local labor markets were 2.4 percent lower in the post-period compared to control firms in the same tercile of S&P 500 share. In comparison, the estimated average treatment effect was only 0.8 percent for treated local labor markets with employment shares of S&P 500 incumbents falling in the bottom tercile. This heterogeneity result lends further credibility to our DiD estimation strategy.

Our results on employee earnings could be consistent with classical monopsony model or other models of employer market power. The classical monopsony model predicts that increased common ownership would reduce total employment while other models—for example [Jarosch, Nimczik and Sorkin \(2021\)](#)—show that changes in employer market power could affect employee earnings without affecting employment levels. However, we examine the effects of S&P 500 shocks on total employment of nonfocal firms and find that total employment of nonfocal firms *increased* in treated local labor markets after S&P 500 shocks relative to control local labor markets.

To try to understand this positive effect on employment, we examine the effect of common ownership on the hiring and separating rates in treated labor markets. We find that the separation rate increased, consistent with lower wages making the jobs at the affected firms less attractive. However, we also observe an even larger increase in the hiring rate in treated local labor markets, which explains (in a proximate way) why employment increased *despite* the higher separation rate. This suggests that firms in treated markets were able to (and had an incentive to) increase their employment level—despite having lower wages—by increasing their recruiting intensity.

These empirical facts are not consistent with prior models of labor market power that we are aware of. However, we show that one *can* rationalize our empirical findings in a model of oligopsony in which the supply of workers to a firm is a function not only of its wage, but also of its expenditure on recruitment ([Forsythe and Weinstein, 2021](#)).⁴ When common ownership among the firms hiring labor in a market increases, it reduces wages, but the effect on recruiting intensity is ambiguous. On one hand, the firms have less incentive to spend on recruiting, because increasing recruiting leads to more competition with other firms with which they have common ownership. On the other hand, since equilibrium wages are lower, profits per recruited employee are higher, which increases the incentive to spend resources on recruiting relative to the equilibrium without common ownership. The effect of common ownership on equilibrium recruiting intensity and employment can be positive or negative, depending on the parameters of the model.

⁴Thus, one can think of our model as extending the “generalized model of monopsony” of [Manning \(2006\)](#) from a one-firm setting to a multifirm setting with strategic interaction.

This paper builds off two strands of literature. First, it adds to the literature on the real effects of common ownership, making two contributions. The first contribution is providing the first measures of common ownership at the local labor market level. Average local labor market common ownership has more than doubled between 1999 and 2017, increasing from 1.9 percentage points to 4 percentage points. The second contribution is providing evidence on the causal effects of common ownership on employee earnings at the local labor market level. Prior studies focus on the effects of common ownership on product markets (see, for example, [Azar, Schmalz and Tecu, 2018](#); [Newham, Seldeslachts and Banal-Estanol, 2018](#); [Ruiz-Pérez, 2019](#); [Backus, Conlon and Sinkinson, 2021a](#)), executive compensation ([Antón et al., n.d.](#)), and innovation ([López and Vives, 2019](#); [Antón et al., 2021](#)), but little is known about its effects on labor markets. This paper starts to fill this gap, and the results suggest that common ownership leads to lower employee earnings in local labor markets. To the best of our knowledge, this is the first empirical evidence on the effects of common ownership on local labor markets. With the availability of the common ownership measure at the local labor market level, future research can shed more light on how common ownership affects labor market outcomes beyond the outcomes we consider in the paper.

The paper also relates to the literature on imperfect competition in labor market. The labor economics literature has generally found that firms face upward sloping labor supplies, indicating the existence of monopsony power ([Ashenfelter, Farber and Ransom, 2010](#); [Manning, 2011](#); [Staiger, Spetz and Phibbs, 2010](#); [Falch, 2010](#); [Ransom and Sims, 2010](#); [Matsudaira, 2013](#); [Goolsbee and Syverson, 2019](#); [Dube et al., 2020](#); [Manning, 2021](#); [Bassier, Dube and Naidu, 2022](#)). Some prior studies measure labor market power by employer concentration, in particular, the Herfindahl-Hirschman Index (HHI) based on either job posting share ([Azar, Marinescu and Steinbaum, 2020](#)) or employment share ([Benmelech, Bergman and Kim, 2020](#); [Prager and Schmitt, 2021](#); [Rinz, 2020](#); [Arnold, 2021](#); [Qiu and Sojourner, 2019](#)). The conclusion from these studies is that HHI in a labor market is negatively associated with employee earnings at the market or establishment level. But employer concentration is only one source of employer market power and is far from the only one. For example, search friction or job differentiation can give firms wage-setting power, even in unconcentrated markets ([Manning, 2021](#); [Card et al., 2018](#); [Azar, Berry and Marinescu, 2019](#)). While we find new evidence that common ownership increased in recent decades, these papers show that employment concentration has not. We contribute to this literature by showing that, holding the structure of a labor market as constant, rising connections among firms via common shareholders may have increased employer market power in the United States in recent decades.

2 Data Description

2.1 Labor Market Definition

We follow [Rinz \(2020\)](#) and define a labor market as the interaction between a CZ (2000 version) and a four-digit NAICS industry (2012 version). A CZ is a cluster of contiguous counties that reflect the local economies where people live and work. There are 709 CZs (2000 version) in the United States. Another choice of the geographic area in the labor market definition is a core-based statistical area (CBSA), which are also clusters of contiguous counties. An average CBSA is smaller than an average CZ since CBSAs exclude a large fraction of the United States, especially in the Midwest and West regions. We show later that our results are robust if the geographical borders of labor markets are delineated by CBSAs.

2.2 Local Labor Market Common Ownership

To measure common ownership at the local labor market level, we combine data on employment share of each firm in a local labor market with data on institutional ownership at the firm level. To measure employment share of a firm in a local labor market, we use establishment-level employment data from Data Axle Business Data (Data Axle hereafter). Data Axle is a business-to-business marketing company and provides data on almost every business in the United States and Canada.⁵ Our access to Data Axle starts in 1997 and ends in 2018. Between 1997 and 2018, Data Axle on average covers 13.5 million establishments annually, with 11.3 million establishments surveyed in 1997, and the number increases to 14.7 million in 2018. For each surveyed establishment, Data Axle reports employment, sales, 2012 version six-digit NAICS industry, geographic location (longitude, latitude, zip code, county, and state), and ultimate parent company. Data Axle verifies establishment-level employment data by a phone survey process. Each establishment is assigned a unique identifier by Data Axle, the ABI number, which stays constant even if the ownership of an establishment changes. We drop establishments with only one employee from the sample, as our data source on earnings excludes nonemployer establishments. We match the ultimate parent firms in Data Axle to publicly traded firms in the Center for Research in Security Prices (CRSP) by firm names by using a fuzzy name-matching procedure. An ultimate parent firm in Data Axle is uniquely matched to one firm identifier in CRSP, PERMCO, in each year.

Data on institutional ownership (IO) of U.S. publicly traded firms are from [Backus, Con-](#)

⁵The Data Axle Business Data website is available at <https://www.data-axle.com/our-data/business-data/>.

lon and Sinkinson (2021b).⁶ In the United States, all institutional investment managers with at least \$100 million in assets under management are required to file the Securities and Exchange Commission’s (SEC) Form 13F and disclose information on their securities holdings. Backus, Conlon and Sinkinson (2021b) scrape the IO data from 13F files directly, and the data are available between the first quarter of 1999 and the third quarter of 2017. For the “Big Three” (BlackRock, Vanguard, and State Street) and Barclays, we follow Backus, Conlon and Sinkinson (2021b) and aggregate ownership data to the fund family level based on the asset manager’s name in the data.

Combining IO data from Backus, Conlon and Sinkinson (2021b) with firms’ local labor market employment share calculated from Data Axle, we measure common ownership in each local labor market each year. We use information on both publicly traded and privately held firms when constructing the measure. Suppose there are J_m employing firms in a local labor market m . Let ω_j be the employment share for firm j in local labor market m . For each shareholder s , let β_{js} be shareholder s ’s ownership share in firm j . If firm j is not publicly traded, then $\beta_{js} \equiv 0$. We maintain a proportional control assumption so that shareholder s ’s voting share is equal to its control share. For any two firms j and k , their degree of common ownership is $\lambda_{j,k} = \frac{\sum_s \beta_{js} \beta_{ks}}{\sum_s \beta_{js} \beta_{js}}$. If either firm j or k is not publicly traded or not held by any institutional investors, then $\lambda_{j,k} = 0$. Then, common ownership in a local labor market, λ_m , is

$$\lambda_m = \sum_{j=1}^{J_m} \left(\sum_{k \neq j} \frac{\omega_j \omega_k}{1 - \omega_j} \times \lambda_{j,k} \right), \quad (2.1)$$

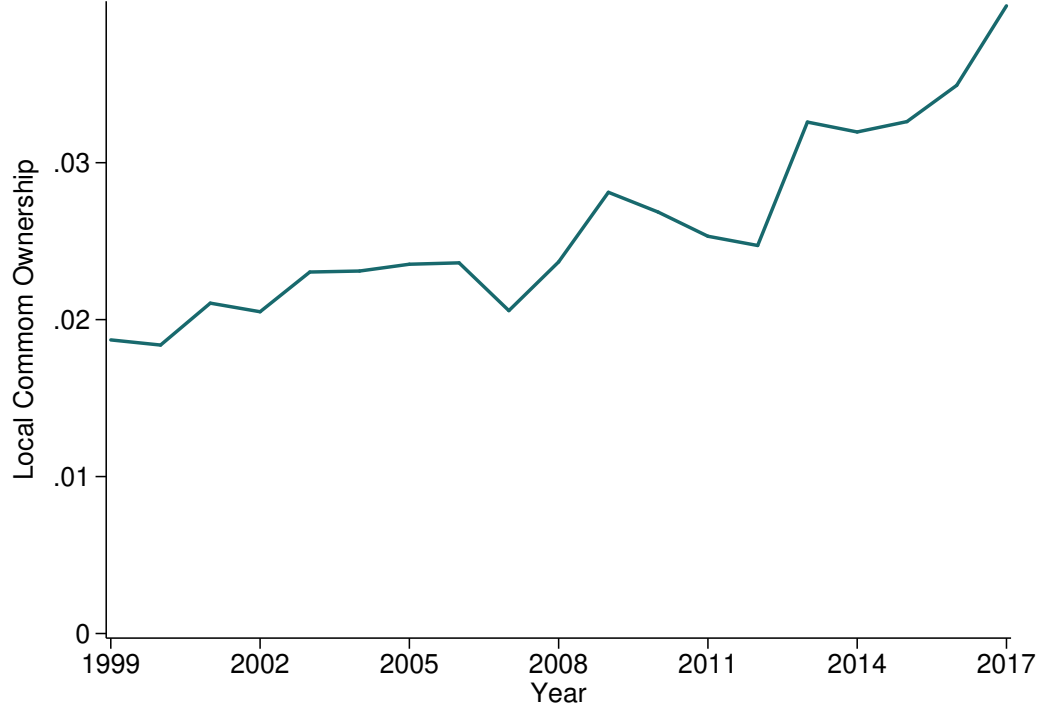
where $\lambda_{j,k}$ measures the connection between any two firms j and k via common ownership across institutional shareholders. Given that institutional ownership data are at the quarterly level, we first calculate local industry-level common ownership measure in each quarter and then take the simple average across all quarters in a year to construct the annual measure.

Figure 1 reports the trend of local labor market-level common ownership between 1999 and 2017. In each year, we calculate the Data Axle employment-weighted average of the common ownership across local labor markets. The figure shows that common ownership at the local labor market level has trended up over the period 1999–2017. In 1999, the average local common ownership is 0.019, and it more than doubles to 0.04 in 2017.

⁶The IO data are available at <https://sites.google.com/view/msinkinson/research/common-ownership-data>.

Figure 1. Common Ownership in Local Labor Markets: 1999–2017

This figure reports the trend of common ownership at the local labor market level between 1999 and 2017. In each year, we calculate the Data Axle employment-weighted average common ownership across local labor markets.



2.3 Earnings

To measure average earnings per employee in each local labor market each year, we use data on total payroll and total employment at the county \times four-digit NAICS industry from the annual average files of the Quarterly Census of Employment and Wages (QCEW). The NAICS industry codes in QCEW change versions over time, and we harmonize all four-digit NAICS codes to the 2012 version.⁷ This procedure produces a measure of total payroll and total

⁷In QCEW, data from 1990 to 2006 uses the 2002 version NAICS, from 2007 to 2010 it uses the 2007 version NAICS, from 2011 to 2016 it uses the 2012 version NAICS, and from 2017 forward it uses the 2017 version NAICS. We harmonize all four-digit NAICS codes to the 2012 version. Concordances between the 2002 or 2007 version and the 2012 version NAICS is available at <http://www.fpeckert.me/cbp/>. If a 2002 or 2007 four-digit NAICS code splits into multiple 2012 codes, then we estimate the payroll and employment in a county \times 2012 NAICS code \times year cell as the original value times the corresponding weight provided in the concordance. The concordance between the 2017 and the 2012 version NAICS is available at <https://www.census.gov/naics/?68967>. If one 2017 NAICS code splits into multiple 2012 codes, then we assign an equal weight to each split, and estimate the payroll and employment in a county \times 2012 NAICS code \times year cell as the original value times the assigned weight.

employment at the county \times 2012 version four-digit NAICS industry level that is consistent over time. We aggregate payroll and employment data at the county \times four-digit NAICS level up to the CZ level to measure them at the local labor market level. Average annual earnings per employee in a local labor market is defined as the ratio of payroll to employment.

3 Difference-in-Differences Analysis

To further mitigate endogeneity concerns in panel regressions, we exploit a potentially exogenous shock to local labor market common ownership induced by firms' additions to the S&P 500 index and estimate causal effects of common ownership on annual earnings per employee at competitor firms. Section 3.1 introduces the details of research design, and Section 3.2 reports the estimation results.

3.1 Empirical Specification

[Boller and Scott Morton \(2020\)](#) propose to use the addition of a firm to the S&P 500 index (focal firm) as a shock to common ownership of its *industry competitors* (nonfocal firms). They show that a firm entering the S&P 500 index experiences a sharp increase in institutional ownership, leading to an increased overlap between the firm and its publicly traded industry competitors via common owners. As a result, the average common ownership of nonfocal firms in a local labor market tends to increase after focal firms enter the S&P 500 index. More importantly, a focal firm's addition to the index does not change the nature of operations and products of nonfocal firms and is also unlikely to alter nonfocal firms' visibility to institutional investors or analysts. This strategy has also been used in [Antón et al. \(n.d.\)](#) to study the effect of common ownership on CEO compensation structure.

To draw causal inferences on whether and how common ownership affects employee earnings, we examine how the average annual earnings per employee of nonfocal firms in a local labor market changes after focal firms are added to the S&P 500 index, compared to the one in local labor markets where firms never enter or exit the index in the sample. For each index addition event, we choose the estimation window to be five years around the event. The data on the starting and ending dates of a firm in the S&P 500 index are from Compustat. Given that our common ownership measure is available between 1999 and 2017, we use index addition events between years 2004 and 2012. We call firms entering the S&P 500 index in the same year as being in the same cohort. There are 192 index addition events across the nine cohorts in our sample. Each firm-level index addition generates heterogeneous treatment shocks across local labor markets, depending on the interaction between firms' local employment shares and

common ownership arrangements. Combining data on index addition events with data on the locations, employment, and parent firms of establishments in Data Axle, we can measure induced variation in common ownership shocks across local labor markets.

A local labor market is defined to be treated in a cohort if it satisfies the following three conditions during the year of an index addition event: 1) there exists at least one firm that enters the S&P 500 index; 2) there is no firm that exits the S&P 500 index; and 3) there is at least one firm that has already been in the S&P 500 index. To avoid multiple, sequential shocks in the same local labor market, which can muddy the treatment status of a given local labor market and year, if a treated local labor market also experiences other index addition or exit events within the estimation window, we exclude it from the sample. A local labor market is defined to be a control local labor market in a cohort if there is no firm that enters or exits the S&P 500 index between 1997, the first year we have access to Data Axle, and the end of the estimation window.

To measure the effect of local common ownership on employee average annual earnings, we want to exclude employees of the focal firm that was added to the S&P 500 index, which is challenging without firm-level earnings data. We use QCEW data to construct annual earnings per employee among nonfocal firms in a local labor market.⁸ We use the Data Axle firm employment data to identify all county \times four-digit NAICS cells where the focal firm has employees, and we exclude these cells when aggregating up QCEW data on counties in the CZ to measure local labor market employment and earnings. This excludes focal firm employment and earnings (along with some proximate nonfocal firm analogues). Our main outcomes are based exclusively on employment and earnings in the nonfocal firms in the same CZ-industry but not the same counties-industry as the focal firm. By excluding the most direct, geographically proximate competitors and looking at effects only among more-remote competitors, we expect this test to be conservative and, perhaps, underestimate effects.

A CZ is a cluster of counties, but the composition of counties in a CZ \times four-digit NAICS with non-missing payroll and employment data may change over time. To avoid this composition issue within a local labor market, we therefore focus on county \times four-digit NAICS cells with balanced panels of observed QCEW payroll and employment.⁹ The restriction focuses the analysis on cells with employment above the lowest levels.

For a treated local labor market, we first define focal cells as county \times five-digit NAICS cells

⁸Data Axle provides information on employment but not payroll at the establishment level.

⁹Census's data disclosure protection rules lead them to suppress QCEW reporting of employment and payroll in county-industry-years with few employers. For never-tiny (never-suppressed) cells that contain most employment, this is not an issue and these are the cells we focus on. For always-tiny, always-suppressed cells, we have no choice; but they account for little employment. This issue has bite only for marginal cells that switch in or out of data suppression. Excluding these excludes cells that have both employment rises and employment declines.

to which focal firms belong and define nonfocal cells as county \times five-digit NAICS cells that do not contain any focal firm. If all focal cells have balanced panels of payroll and employment within the estimation window, we then subtract payroll (employment) of all focal cells from payroll (employment) in a county \times four-digit NAICS cell; otherwise, we use the sum of payroll (employment) of nonfocal cells with balanced panels of payroll (employment) within the estimation window. After performing this procedure, the data on payroll and employment at the county \times four-digit NAICS level are clean; they do not contain any information of any focal firm.

For each cohort, we restrict our sample to county \times four-digit NAICS industries with balanced panels of strictly positive payroll, total employment, and publicly traded and privately held firms' employment within the estimation window. We then aggregate all these outcomes to the CZ \times four-digit NAICS level. To be consistent with the way other variables are constructed, we recalculate the average common ownership in a local labor market for nonfocal firms with operations in the above-mentioned county \times four-digit NAICS cells.

We use a difference-in-differences (DiD) design to estimate the treatment effects of S&P 500 index additions on average annual earnings per employee of nonfocal firms in a local labor market. In the raw data, the parallel trends assumption is violated. Therefore, we employ a matched DiD estimator and it involves two steps. In the first step, we match each treated local labor market to a set of control local labor markets within each cohort. Specifically, we run a linear regression in each cohort by regressing a local labor market's treatment status on a list of pretreatment variables. We then match each treated local labor market to the 10 nearest control local labor markets based on the estimated propensity scores. We further require the absolute value of the difference in propensity scores between a treated and a control local labor market, the caliper, to be less than or equal to 0.1 percent. In Section 3.2.3, we show that our results are robust to alternatives choices of the number of matched control local labor markets or the calipers.

The list of pretreatment variables used in matching includes change in local common ownership, change in the natural logarithm of average annual earnings per employee, and change in total employment in each year during the four-year period before index addition events. Matching on these time-varying characteristics helps identify control local labor markets such that the trends of these key outcomes are parallel between treated and control local labor markets before treatment. In addition, we also include the pretreatment mean of local labor market and CZ characteristics in the list to estimate propensity scores. Characteristics at the local labor market level include distribution (10th, 25th, median, 75th, and 90th percentiles) of the natural logarithm of establishment employment, employment share of publicly traded firms, average total institutional ownership, and average top five institutional ownership, all of which are cal-

culated based on Data Axle data. Characteristics at the CZ level include population density, unemployment rate, demographics (shares of female, whites, blacks, Hispanics, people with ages between 20 and 24, between 45 and 64, and greater than or equal to 65), the extent to which a CZ is subject to the right-to-work (RTW) law, and enforcement level of noncompete agreement (NCA) in a CZ.

These are measured as follows. Population density at the CZ \times year level is defined as population per square mile and is calculated based on the Census Gazetteer files at the county \times year level.¹⁰ Unemployment rate at the CZ \times year level is calculated based on county \times year-level data from Local Area Unemployment Statistics (LAUS) program through the Bureau of Labor Statistics (BLS).¹¹ Demographics at the CZ \times year level are calculated based on county \times year-level data from Surveillance, Epidemiology, and End Results (SEER) Program.¹² To measure the extent to which a CZ is subject to the RTW law in a year, we calculate the average RTW law adoption dummies of all the states in the CZ weighted by the state population share in the CZ (measured in year 2000). Data on state-level RTW law adoptions are from [Knepper \(2020\)](#). To measure the NCA enforcement level in a CZ in a year, we calculate the average NCA enforcement index of all the states in the CZ weighted by the state population share in the CZ (measured in year 2000). Data on state-level NCA enforcement index are from [Marx \(Forthcoming\)](#). There are 31 matching variables in total. We have 2,090 pairs of matched treated and control local labor markets in the sample. Table 1 reports the pretreatment mean of outcome variables as well as local labor market and CZ characteristics for treated and control local labor markets.

In the second step, we estimate average treatment-effect-on-treated of S&P 500 index additions on employee earnings. Following [Cengiz et al. \(2019\)](#), we first stack the observations across all matched pairs and then run the following regression by including matched pair \times local labor market and matched pair \times year fixed effects. There are at least two advantages of this specification. First, it aligns matched pairs of treated and control local labor markets by event time, and this is equivalent to a setting in which all the events happen at the same time rather than being staggered over time. Second, we use “clean controls” in the sense that control local labor markets have not been treated yet by the end of estimation window. Using this specification would mitigate the concerns in [Goodman-Bacon \(2021\)](#) on using the canonical two-way fixed effects model to estimate treatment effects in a DiD setting and is in a similar spirit to the method proposed in [Callaway and Sant’Anna \(2021\)](#).

¹⁰Census Gazetteer files are available at <https://www.census.gov/programs-surveys/geography/technical-documentation/records-layout/gaz-record-layouts.html>.

¹¹LAUS data are available at <https://www.bls.gov/lau/>.

¹²SEER data are available at <https://seer.cancer.gov/popdata/download.html>.

$$y_{p(k)cit} = Treated_{p(k)ci} \times \sum_{n=-5 \& n \neq -1}^5 \beta_n \times \mathbb{1}(t - t_k = n) + \mu_{p(k)ci} + \eta_{p(k)t} + \epsilon_{p(k)cit}, \quad (3.1)$$

where c , i , and t index for CZ, four-digit NAICS industry, and year, respectively. $p(k)$ indexes for a matched pair of a treated and control local labor markets in cohort k . $y_{p(k)cit}$ is the natural logarithm of average annual earnings per employee in local labor market (ci) in year t of matched pair $p(k)$. The coefficients of interest are β_n . The estimated coefficients capture the dynamics of the relative outcome between treated and control local labor markets over time. The omitted category is $n = -1$, the year immediately before an index addition event. β_n is interpreted as the average relative change in an outcome between local labor markets in treated and control groups across all pairs during time n , relative to time -1 . If outcomes in treated and control local labor markets are on similar trends before index addition events, then β_{-5} , β_{-4} , β_{-3} , and β_{-2} would be small in magnitude and statistically insignificant.

To estimate the average treatment effect, we estimate the following regression:

$$y_{p(k)cit} = \beta \times Treated_{p(k)ci} \times \mathbb{1}(t - t_k > 0) + \mu_{p(k)ci} + \eta_{p(k)t} + \epsilon_{p(k)cit}. \quad (3.2)$$

The parameter of interest is β and it measures the average change in the outcome variable in treated local labor markets relative to that in control local labor markets.

3.2 Estimation Results

3.2.1 Main Results

In this subsection, we report the estimated results on the effects of S&P 500 index additions on the average common ownership and average annual earnings per employee of nonfocal firms in a local labor market.

We start with the estimation of Equation (3.1) for average common ownership of nonfocal firms in a local labor market. The results are reported in Figure 2 and columns (1) and (2) of Table A.2. The results show that the trajectories of common ownership among nonfocal firms in treated and control local labor markets are parallel before focal firms' additions to the S&P 500 index. During the posttreatment period, we observe a significant increase in the average common ownership of nonfocal firms in treated local labor markets relative to control local labor markets. The common ownership of nonfocal firms on average increases 0.4 percentage points and it is statistically significant at 1 percent level. Given that the sample average of common ownership of nonfocal firms during the pretreatment period is 2.2 percentage points,

the estimated average treatment effect is economically meaningful and represents an 18 percent increase. The results confirm that focal firms' additions to the S&P 500 index indeed lead to an increase in the average common ownership of nonfocal firms in a local labor market, and the results are consistent with the evidence in [Boller and Scott Morton \(2020\)](#).

We next report the estimation of Equation (3.1) for average annual earnings per employee among nonfocal firms in a local labor market. The results are in Figure 3 and columns (3) and (4) of Table A.2. The estimated coefficients during the pretreatment period are close to zero and statistically insignificant, adding credibility to the maintained parallel trends assumption posttreatment. The trajectories of average annual earnings per employee in nonfocal firms between treated and control local labor markets only start to diverge since the first year after treatment. Average annual earnings per employee of nonfocal firms decreases 1.1 percent relative to control local labor markets after focal firms enter the S&P 500 index, and it is statistically significant at the 1 percent level. Given that the average nonfocal firms' annual earnings per employee in treated local labor markets during the pretreatment period is \$44,317, our estimate suggests that an average employee of nonfocal firms in treated local labor markets earns \$487 less per year, or \$2,437 in total relative to the counterfactual during the first five years after treatment. Figure 3 also shows that estimated effect becomes stronger over time. During the first year after treatment, the estimate shows that the average annual earnings per employee is 0.8 percent lower in treated local labor markets relative to the counterfactual. By the fifth year after treatment, the magnitude of the estimated negative effect increases to 1.7 percent.

3.2.2 Heterogeneity

In addition to the baseline estimates on employee earnings, we examine heterogeneous effects of treatment intensity. We proxy the treatment intensity in a treated local labor market by the employment share of S&P 500 index incumbents, the publicly traded firms that are already in the S&P 500 index, during the event year (*S&P500Share*). We expect the estimated effects on the average annual earnings per employee to be larger for treated local labor markets with higher employment shares of S&P 500 incumbents.

We split the treated local labor markets into terciles based on *S&P500Share*. For each treated local labor market in a tercile, we reimplement the procedure described in Section 3.1 and match it to a set of control local labor markets. We then reestimate Equation (3.1) for each subsample and report the results in Figure 4 and Table A.3. The estimates are consistent with our expectations. For treated local labor markets with *S&P500Share* falling in the top tercile, the estimated effect is the largest. The average annual earnings per employee of nonfocal firms in treated local labor markets is 2.4 percent lower compared to the counterfactual. In contrast, for

treated local labor markets with *S&P500Share* falling in the bottom tercile, the estimated coefficient on $\text{Treated} \times \text{Post}$ is 0.8 percentage points and is statistically insignificant. The difference between these two estimates is statistically significant at the 1 percent level.

Table 1. Summary Statistics of Outcome Variables and Covariates in DiD Analyses

This table reports the (unweighted) summary statistics of pretreatment average of outcome variables and covariates in the DiD analysis. Annual earnings per employee is in 2019 dollars. Variable definitions are available in Appendix A. Standard errors are double clustered at the four-digit NAICS and CZ level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	N	Treated	Control	Difference
Outcome Variables				
Common Ownership	2,090	0.022	0.018	0.004
Log(Annual Earnings per Employee)	2,090	10.527	10.562	-0.035
Log(Total Employment)	2,090	6.392	6.107	0.285
Local Labor Market Characteristics				
10th Percentile of Log(Estab Emp)	2,090	0.855	0.871	-0.016
25th Percentile of Log(Estab Emp)	2,090	1.240	1.262	-0.022
50th Percentile of Log(Estab Emp)	2,090	1.717	1.750	-0.034
75th Percentile of Log(Estab Emp)	2,090	2.408	2.450	-0.042
90th Percentile of Log(Estab Emp)	2,090	3.240	3.289	-0.049
Share of Public Firms' Emp	2,090	0.261	0.281	-0.019
Total Institutional Ownership	2,090	0.152	0.163	-0.011
Top 5 Institutional Ownership	2,090	0.057	0.061	-0.005
CZ Characteristics				
Population Density	2,090	295.516	256.603	38.914
Unemployment Rate	2,090	0.056	0.056	0.000
% Female	2,090	0.508	0.508	0.000
% Whites	2,090	0.832	0.832	0.001
% Black	2,090	0.123	0.122	0.001
% Hispanics	2,090	0.106	0.107	-0.001
% Age ≥ 20 & ≤ 44	2,090	0.344	0.344	-0.000
% Age ≥ 45 & ≤ 64	2,090	0.250	0.249	0.000
% Age ≥ 65	2,090	0.130	0.130	0.000
RTW	2,090	0.489	0.493	-0.004
NCA Enforcement Index	2,090	341.080	340.143	0.936

Figure 2. Effect of S&P 500 Index Additions on Common Ownership

This figure reports the estimates of Equation (3.1) for common ownership at the local labor market level. The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.

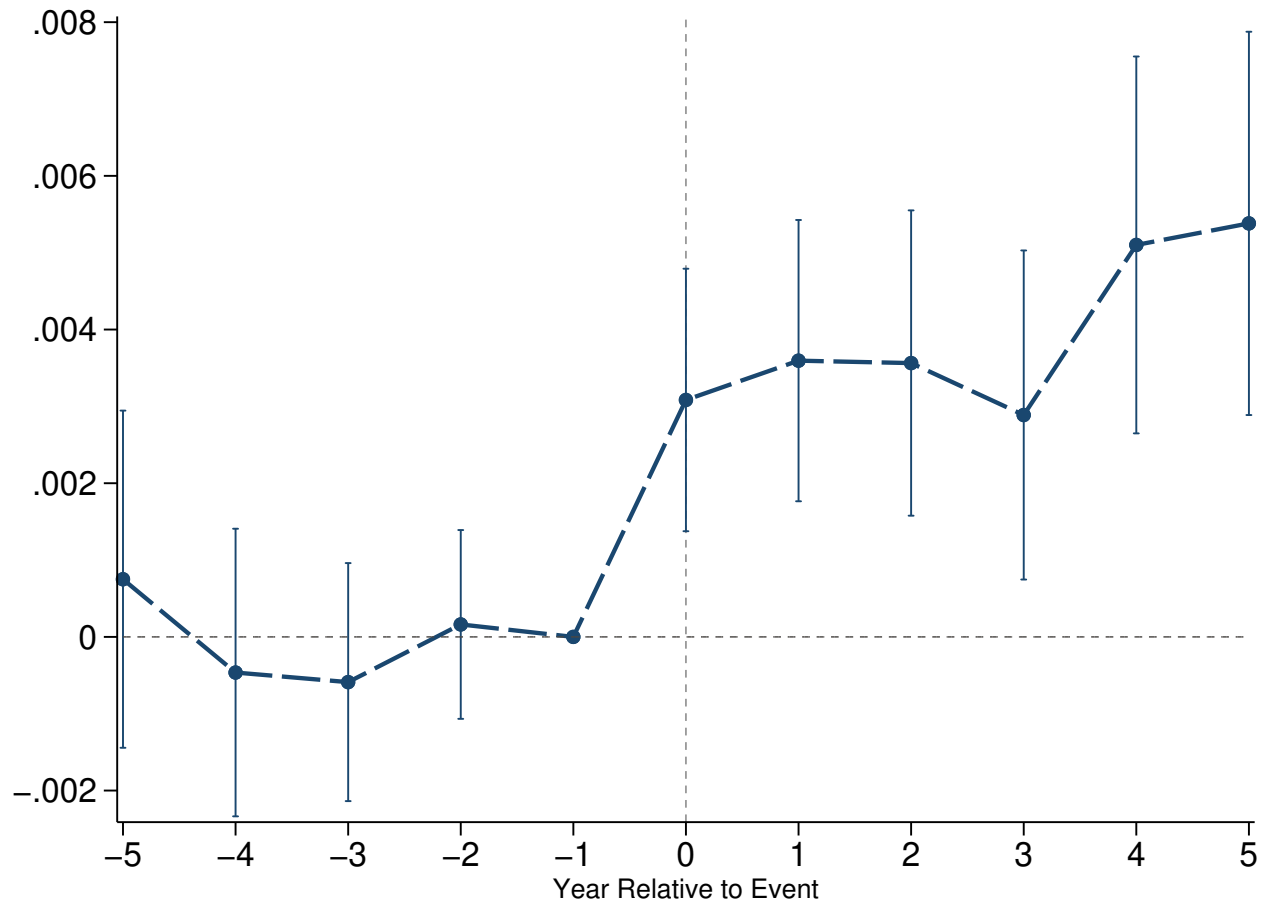


Figure 3. Effect of S&P 500 Index Additions on Employee Earnings

This figure reports the estimates of Equation (3.1) for annual earnings per employee at the local labor market level. The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.

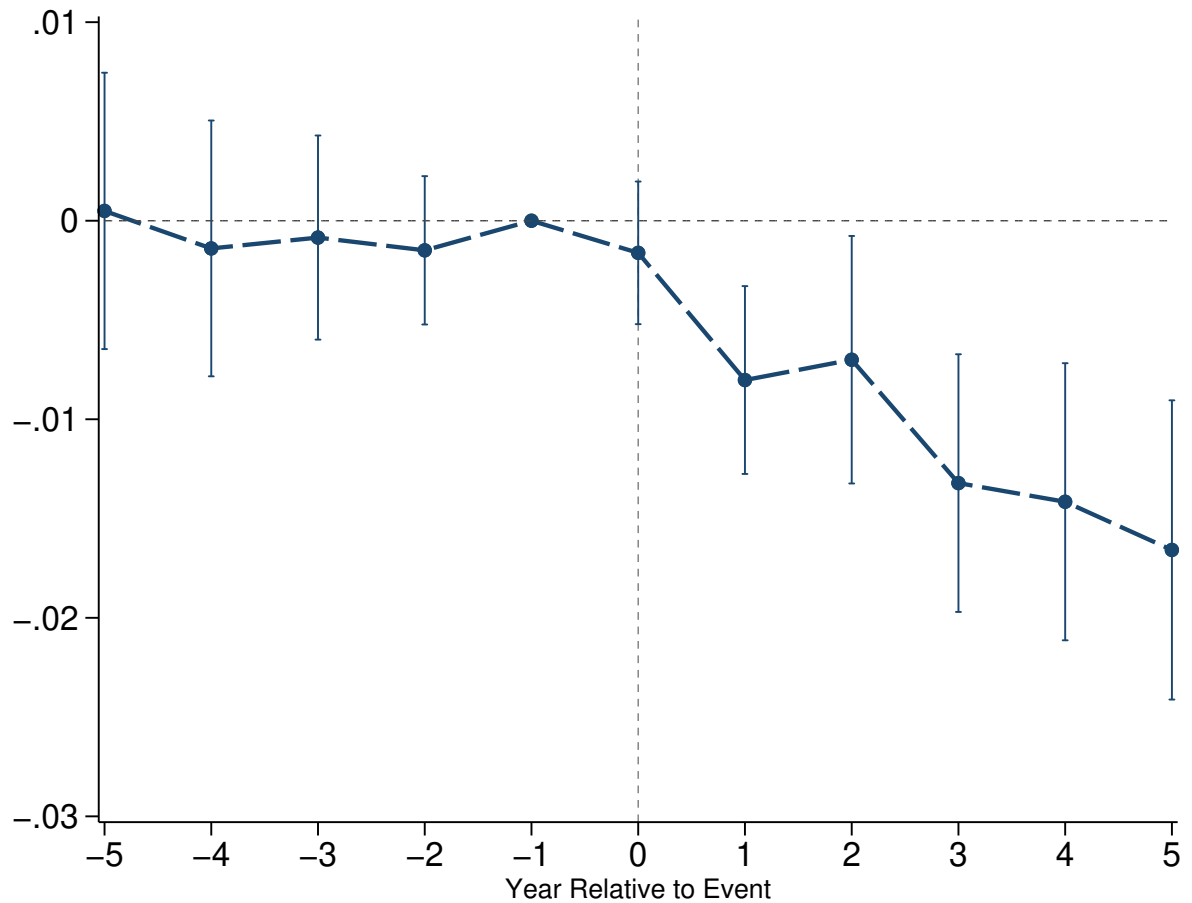
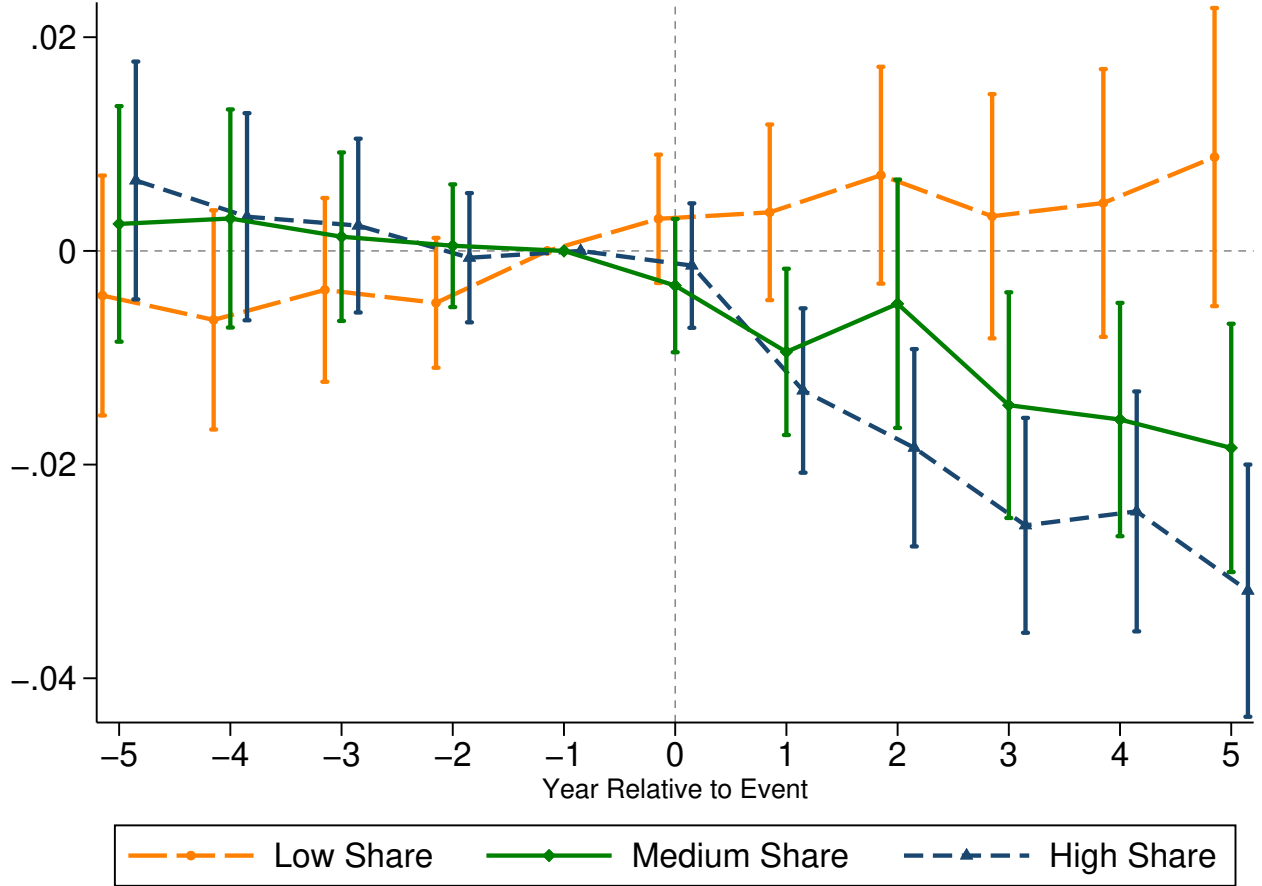


Figure 4. Heterogeneous Effects on Employee Earnings by Employment Share of S&P 500 Incumbents

This figure reports the estimates of Equation (3.1) for annual earnings per employee at the local labor market level conditional on the employment share of S&P 500 incumbents during the year of an index addition event. The bars around point estimates represent 95% confidence intervals and are based on standard errors clustered at the local labor market level.



3.2.3 Robustness

In this subsection, we perform three robustness tests. First, we report estimation results for alternative numbers of control industries matched to a treated local labor market and alternative choices of the caliper. The results are reported in Table A.5. In column (1), a treated local labor market is still matched to 10 control local labor markets with the closest propensity scores but we do not make any restriction on the caliper. In columns (2) and (3), a treated local labor market is matched to 15 control local labor markets with the closest propensity scores. We set the caliper at 0.1 percent in column (2) but do not make any restriction on caliper in column (3). In columns (4) and (5), a treated local labor market is matched to 5 control local labor markets

with the closest propensity scores. We set the caliper at 0.1 percent in column (4) but do not make any restriction on the caliper in column (5). The estimated effects for common ownership and annual earnings per employee in nonfocal firms in a local labor market are very similar to the ones in Table A.2.

Second, we include CZ fixed effects instead of including a list of pretreatment CZ-level characteristics when estimating propensity scores. The estimated results for common ownership and average annual earnings per employee of nonfocal firms in a local labor market are reported in Figure A.1 and Table A.6. Results are robust. Compared to control local labor markets, common ownership of nonfocal firms increases 0.4 percentage points, while employee earnings are 0.9 percent lower after focal firms are added to the S&P 500 index.

Third, we calculate common ownership at the local labor market level using institutional ownership data from the Thomson Reuters 13F database (13F data) and reestimate Equation (3.1). These data are from the Wharton Research Data Services, and we correct the errors in 13F data using the methods in Ben-David et al. (2021). We use data between 1997 and 2018, a period during which we have access to Data Axle, and there are 12 cohorts of S&P 500 index addition events. The estimated results for common ownership and average annual earnings per employee in nonfocal firms in a local labor market are reported in Figure A.2 and Table A.7. Our results are robust to using this alternative source of institutional ownership data.

Fourth, we use an alternative definition of local labor market. We here define a local labor market as the interaction between a CBSA (2013 version) and a four-digit NAICS industry (2012 version). We reimplement the procedure described in Section 3.1. The results are reported in Figure A.3 and Table A.8. Results are robust to this alternative definition of local labor market.

Finally, as a robustness check, we estimate the effects of common ownership on employee earnings in a local labor market using ordinary least square (OLS) and two-stage least square (2SLS) panel regressions, based on all local labor markets over the period 1998–2019. Our instrumental variable (IV) for common ownership in a local labor market is the average of the equally weighted local common ownership for the same industry in other CZs in a given year (Azar, Marinescu and Steinbaum, 2020; Rinz, 2020). The main identification assumption in our IV analysis is that ownership itself is exogenous, which is commonly assumed in the structural common ownership literature (see, for example, Backus, Conlon and Sinkinson, 2021a; Ruiz-Pérez, 2019). This IV purges our explanatory variable of any idiosyncratic variation in local common ownership or variation that is driven by changing labor market shares, and focuses on the part of variation that is driven by nationwide changes in common ownership. Both OLS and 2SLS results suggest that an increase in common ownership in a local labor market is associated with lower annual earnings per employee, but the magnitudes of 2SLS estimates are much larger. In the specification with local labor market and CZ×year fixed effects, OLS esti-

mates suggest that a one-standard-deviation increase in local common ownership is associated with a 0.31 percent decrease in annual earnings per employee, while IV estimates imply a one-standard-deviation increase in common ownership reduces employee earnings by 1.21 percent, or \$518 per year. As in [Azar, Marinescu and Steinbaum \(2020\)](#) and [Rinz \(2020\)](#), a concern with the IV analysis is that, within industry, local unobservable shocks driving both employee earnings and common ownership could be correlated across CZs. The methodology and results are described in more detail in Appendix C.

3.3 Effects on Workforce Characteristics

Employee earnings effects of S&P 500 index additions could occur by affecting workforce composition. To examine whether this is the case, we utilize data from Quarterly Workforce Indicators (QWI).¹³ QWI is a publicly available data set and its underlying micro data comes from the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau. [Abowd et al. \(2009\)](#) provides a detailed description of how QWI is constructed from LEHD. Different states agreed to share their unemployment insurance data with the LEHD program at different times. As a result, data coverage is uneven across states. For example, the data for California is available since the third quarter of 1991, while the data for Massachusetts only starts since the first quarter of 2010. Compared to QCEW, a main advantage of QWI is that it reports local labor market statistics at the county \times four-digit NAICS level by workers' characteristics (education, age, gender, race, and ethnicity). This allows us to examine whether and how workforce composition changes after S&P 500 index additions in a local labor market. This analysis includes both focal and nonfocal firms.

For each local labor market in a quarter, we calculate workforce characteristics and then take the simple average of each characteristic across quarters in a year. Workforce characteristics in a local labor market include 1) the share of workers with less formal education, no more than a high school degree; 2) the share of young workers whose ages are less than or equal to 35 years; 3) the share of workers female; 4) the share of workers who are not white; and 5) the share of workers Hispanic. We then merge these measures with the sample used in Figure 3. Panel A of Table 2 reports the estimated average treatment effects of S&P 500 index additions on workforce characteristics in a local labor market.

The results show that S&P 500 index additions change workforce characteristics. The DiD analysis estimates that S&P 500 index additions lead to a 0.5 percentage point decrease in the share of workers with no more than high school (Column 1). Given that workers with less formal education tend to earn less, this evidence is inconsistent with the argument that the

¹³QWI data are available at <https://ledextract.ces.census.gov/static/data.html>.

employee earnings effect of S&P 500 index additions could be explained by the shift of workforce toward less educated workers. In columns (2)–(4), we report the estimates on the shares of young, female, and nonwhite workers. Our estimates show that S&P 500 index additions increase the shares of young, female, and nonwhite workers by 0.6, 0.3 and 0.3 percentage points, respectively. Given that young, female, and nonwhite workers on average have lower earnings, these estimates suggest that changes in these workforce characteristics could explain part of the employee earnings effect of S&P 500 index additions. One caveat is that although these estimates are statistically significant, their economic magnitudes are small. Finally, S&P 500 index additions do not have any effect on the share of Hispanic workers (Column 5).

To further assess the extent to which changes in workforce characteristics could explain the employee earnings effect of S&P 500 index additions, we follow [Curtis et al. \(2021\)](#) and perform two more tests. First, we directly control for the endogenous workforce characteristics when estimating the average treatment effect of S&P 500 index additions based on Equation (3.2). The results are reported in Panel B of Table 2. Column (1) reports the baseline DiD estimate and we control for workforce characteristics in columns (2)–(6). The estimates in column (6) show that, after controlling for all workforce characteristics, the estimated coefficient on $\text{Treated} \times \text{Post}$ is -0.009 and statistically significant at 1 percent level. The results suggest that S&P 500 index additions lead to lower employee earnings in treated local labor markets conditional on workforce composition changes.

Second, we perform an analysis based on [Kitagawa \(1955\)](#), [Oaxaca \(1973\)](#), and [Blinders \(1973\)](#) (the Kitagawa-Oaxaca-Blinder decomposition) to directly measure the contribution of the change in each workforce characteristic to the change in employee earnings. The analysis involves three steps. First, for each local labor market, we estimate the marginal effect of a workforce characteristic on the natural logarithm of employee earnings using data in the pre-treatment period. Specifically, for treated local labor markets, we run the following regression:

$$y_{p(k)cit} = \beta^{treated,pre} \times X_{p(k)cit} + \mu_{p(k)ci} + \eta_t + \epsilon_{p(k)cit}, \quad (3.3)$$

For control local labor markets, we run the following regression:

$$y_{p(k)cit} = \beta^{control,pre} \times X_{p(k)cit} + \mu_{p(k)ci} + \eta_{p(k)t} + \epsilon_{p(k)cit}, \quad (3.4)$$

As before, c , i , and t index for CZ, four-digit NAICS industry, and year, respectively. $p(k)$ indexes for a matched pair of a treated and control local labor markets in cohort k . $X_{p(k)ict}$ is a vector including the shares of less educated, young, female, nonwhite, and Hispanic workers.

After estimating $\hat{\beta}^{treated,pre}$ and $\hat{\beta}^{control,pre}$, we then calculate the change in each workforce characteristic in treated and control local labor markets after S&P 500 index additions. We

denote them as $\Delta X^{treated}$ and $\Delta X^{control}$, respectively. Finally, the contributions of workforce characteristics changes to changes in employee earnings are calculated as

$$\hat{\beta}^{treated,pre} \times \Delta X^{treated} - \hat{\beta}^{control,pre} \times \Delta X^{control}$$

Table 3 reports the results. Panel A reports the estimated marginal effects of workforce characteristics on the natural logarithm of employee earnings using pretreatment data. Columns (1) and (2) report the results for treated and control local labor markets, respectively. Panel B reports the estimated contributions of workforce characteristics changes to changes in average earnings per employee. The first and second rows report the changes in workforce characteristics for treated and local labor markets, respectively. The third row reports the estimated contribution of the change in each workforce characteristic. Changes in the shares of less educated and Hispanic workers are predicted to increase employee earnings by 0.256 and 0.182 log points, respectively. Changes in the shares of young, female, and nonwhite workers account for 0.354, 0.093, and 0.106 log points of the decrease in employee earnings. Overall, changes in workforce characteristics account for 10.5 percent $(=(0.354+0.093+0.106-0.256-0.182)/1.1)$ of the changes in employee earnings after S&P 500 index additions.

Table 2. Effects on Workforce Characteristics

Panel A of this table reports the estimates of Equation (3.2) for workforce characteristics at the local labor market level. Panel B reports the estimates of Equation (3.2) after controlling for workforce characteristics at the local labor market level. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Panel A: Effects on Workforce Composition					
	% Less Educated	% Young	% Female	% Non-White	% Hispanic
	(1)	(2)	(3)	(4)	(5)
Treated \times Post	-0.005*** [0.001]	0.006*** [0.001]	0.003*** [0.001]	0.003*** [0.001]	0.000 [0.001]
Pair-Local Labor Market FEs	✓	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓	✓
Adjusted R^2	0.950	0.921	0.982	0.971	0.983
N	241,017	241,083	241,046	241,082	239,449

Panel B: Control for Workforce Composition						
	(1)	(2)	(3)	(4)	(5)	(6)
Treated \times Post	-0.011*** [0.003]	-0.013*** [0.003]	-0.010*** [0.003]	-0.009*** [0.003]	-0.009*** [0.003]	-0.009*** [0.003]
% Less Educated		-0.444*** [0.047]	-0.425*** [0.046]	-0.456*** [0.045]	-0.451*** [0.047]	-0.434*** [0.046]
% Young Workers			-0.410*** [0.027]	-0.381*** [0.026]	-0.377*** [0.026]	-0.373*** [0.026]
% Female				-0.549*** [0.036]	-0.548*** [0.036]	-0.561*** [0.036]
% Non-White					-0.043 [0.058]	-0.043 [0.058]
% Hispanics						-0.154*** [0.058]
Pair-Local Labor Market FEs	✓	✓	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.958	0.958	0.959	0.960	0.960	0.960
N	244,431	241,017	241,017	240,991	240,991	239,366

Table 3. Kitagawa-Oaxaca-Blinder Decomposition Analysis

This table reports the results from the Kitagawa-Oaxaca-Blinder decomposition. Panel A reports the estimated marginal effect of each workforce characteristic on the natural logarithm of earnings per employee based on data in the pretreatment data. The estimated marginal effect of a workforce characteristic, l , is denoted as $\hat{\beta}_l^{treated,pre}$ for treated local labor markets and $\hat{\beta}_l^{control,pre}$ for control local labor markets. Panel B reports the estimated contribution of the change in each workforce characteristic to the employee earnings effects of S&P 500 index additions. The estimated contribution of the change in workforce characteristic l is calculated as $\hat{\beta}_l^{treated,pre} \times \Delta l^{treated} - \hat{\beta}_l^{control,pre} \times \Delta l^{control}$. Standard errors in Panel A are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Panel A: Marginal Effects of Workforce Characteristics					
	Treated local labor markets		Control local labor markets		
	(1)		(2)		
% Less Educated	-0.509***		-0.524***		
	[0.119]		[0.053]		
% Young Workers	-0.190***		-0.269***		
	[0.069]		[0.030]		
% Female	-0.621***		-0.466***		
	[0.088]		[0.040]		
% Non-White	-0.109		-0.018		
	[0.089]		[0.064]		
% Hispanics	0.065		-0.100		
	[0.132]		[0.061]		
Pair-Local Labor Market FEs	✓		✓		
Pair-Year FEs			✓		
Year FEs	✓				
Adjusted R^2	0.984		0.968		
N	12,310		117,118		

Panel B: Contributions of Workforce Characteristics Changes					
	$\Delta\%$ Less Educated	$\Delta\%$ Young	$\Delta\%$ Female	$\Delta\%$ Non-White	$\Delta\%$ Hispanic
Treated Local Labor Markets	-0.004	-0.021	-0.003	0.011	0.011
Control Local Labor Markets	0.001	-0.028	-0.006	0.008	0.011
Contribution	0.256	-0.354	-0.093	-0.106	0.182

3.4 Labor Union Power

If the employee earnings effects of S&P 500 index additions are driven by increases in employers' market power, then stronger labor union power in a local labor market could act as a countervailing force. In this subsection, we examine whether and how labor union power affects the impacts of S&P 500 index additions on employee earnings.

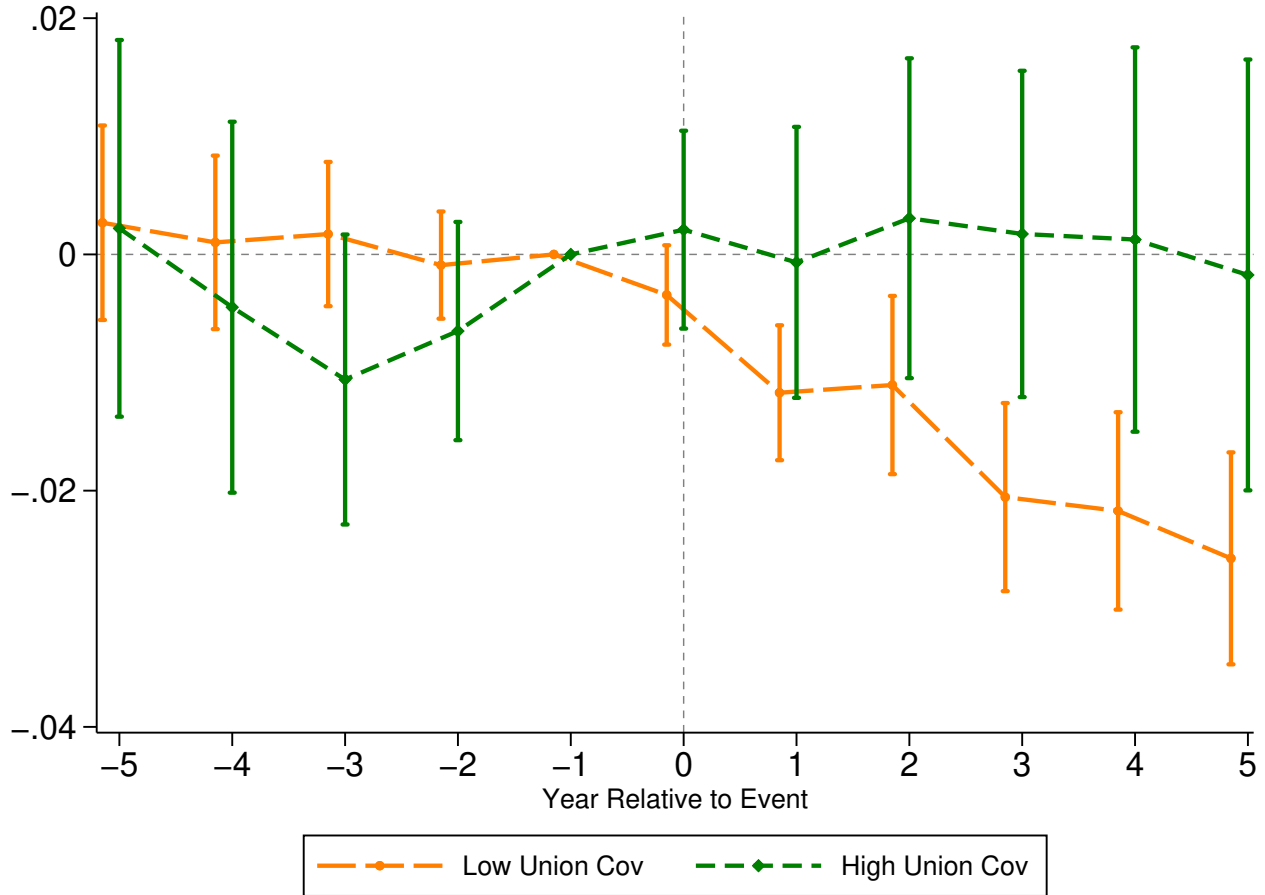
To measure union power at the local labor market level in a year, we rely on data from Current Population Survey (CPS) and estimate union coverage rate at the CZ×NAICS sector level as a proxy.¹⁴ For each year, we first estimate union coverage rate at the State×NAICS sector level weighted by CPS earner weights and then, for each CZ×NAICS sector, union coverage rate is calculated as the average union coverage rates across State×NAICS sector cells weighted by the population share of each state in the CZ.

For each cohort, we split local labor markets into ones with high and low labor union power based on the median of pretreatment mean of union coverage rate and estimate Equations (3.1) and (3.2) for local labor markets with high and low pretreatment union coverage rates separately. We report the results in Figure 5 and Table A.4. The estimates are consistent with our expectations. Among local labor markets with low union coverage rates prior to S&P 500 index additions, the average annual earnings per employee of nonfocal firms in treated local labor markets is 1.8 percent lower compared to the one in control local labor markets. In contrast, among local labor markets with high union coverage rates prior to treatment, the estimated average treatment effect is close to zero and is not statistically significant. The difference between these two estimates is statistically significant at the 1 percent level.

¹⁴The crosswalk between the Census 1990 industry code and NAICS sector is available at <https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html>. The data on NAICS sector=55 are not available in CPS.

Figure 5. Heterogeneous Effects on Employee Earnings by Labor Union Power

This figure reports the estimates of Equation (3.1) for annual earnings per employee at the local labor market level conditional on pretreatment mean of union coverage rate. The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.



3.5 Effects on Total Employment

Our evidence so far shows that an increase in common ownership has a negative impact on average annual earnings per employee in a local labor market. We further show that only a small fraction of this effect can be explained by changes in workforce characteristics. This suggests that employer market power is more likely to be a driving force behind the results. However, it's not clear which model of employer market power the empirical findings best match.

The classical monopsony model (Robinson, 1969) combines employer market power with an internal pay equity constraint. Under these conditions, a monopsonistic employer maxi-

mizes profits by paying workers less than the perfectly-competitive market wage (their marginal product) and employs fewer workers than they would in a competitive equilibrium. If common ownership effected operated along the lines of monopsonistic competition, then we would expect the negative wage effect to be accompanied by lower total employment in treated local labor markets relative to the counterfactual after S&P 500 index additions.

In other models, changes in employer market power could reduce employee earnings without suppressing the employment level. For example, [Jarosch, Nimczik and Sorkin \(2021\)](#) builds a model based on the structure of a canonical search and bargain model but allows for a finite number of firms. As a result, it is possible for a worker to reencounter past employers in the future. In the model, a firm is not a competitor of itself in the future, that is, workers' outside options do not include future vacancies of the firm. Therefore, workers' outside options are worse when bargaining with employers, especially when the distribution of employment is more concentrated, resulting in lower earnings. But their model does not predict "underemployment."

The fact that different models of employer market power with the same prediction of negative wage effects have different predictions for employment levels motivates us to examine the effects of S&P 500 index additions on total employment of nonfocal firms in a local labor market. We estimate Equation (3.1) by replacing the dependent variable as the natural logarithm of total employment. The results are reported in Figure 6 and in Table A.9.

The results show that the total employment of nonfocal firms increases after focal firms are added to the S&P 500 index. The trajectories of total employment between treated and control local labor markets are parallel before treatment. They only start to diverge after index addition events and the estimated effects increase over time. During the posttreatment period, nonfocal firms' total employment in treated local labor markets increases by 2.3 percent relative to the counterfactual.¹⁵

To investigate whether the effect on total employment is driven by more new hires or less separations, we examine the effects of S&P 500 index additions on employment flows. Data on new hires and separations in a local labor market come from QWI. A worker is defined as a new hire for an employer in a quarter if the worker has positive earnings at the employer in the quarter but no earnings in any of the proceeding four consecutive quarters. A worker is defined as a separation from an employer in a quarter if the worker has positive earnings at the employer in the previous and current quarter but no earnings from the employer in the next quarter. In each year, we calculate the total new hires and total separations across four

¹⁵Given that the sample mean of total employment of nonfocal firms in treated local labor markets one year prior to the shock is 1,752, our estimates imply that employment of treated nonfocal firms increases by 40 relative to that of firms in control local labor markets after S&P 500 index additions.

quarters. Hiring rate is defined as the ratio of total new hires in a year to the beginning-of-year employment and separation rate is defined as the ratio of total separations in a year to the beginning-of-year employment. For both calculated ratios, if they are larger than one, then we replace them as missing.

We then repeat the estimation procedure in Section 3.1 and additionally match on the changes in hiring and separation rates during pretreatment period. The results are reported in Figure 7 and Table A.10. The results first show that separation rate in treated local labor markets gradually increases relative to that in control local labor markets after S&P 500 index additions. By the end of fifth year after treatment, compared to control local labor markets, separation rates in treated local labor markets increase 0.6 percentage points, representing a 1.44 percent increase relative to the pretreatment mean of separation rates in treated local labor markets (41.6 percentage points). This result is consistent with the results that S&P 500 index additions lead to a lower employee earnings in treated local labor markets relative to the counterfactual.

The results in Figure 7 further show that hiring rates of treated local labor markets increase even more after S&P 500 index additions. The estimates show that, compared to control local labor markets, hiring rates of treated local labor markets increase 1.2 percentage points by the end of fifth year after treatment, representing a 2.39 percent increase relative to the pretreatment mean of separation rates in treated local labor markets (50.2 percentage points).

Overall, we show that S&P 500 index additions lead to a higher total employment in treated local labor markets relative to the counterfactual. Further, this effect is consistent with more intensive recruiting activities and hiring by firms in treated local labor markets. Our evidence is not consistent with either classical monopsony model, which predicts a lower total employment in treated local labor markets, nor the model in Jarosch, Nimczik and Sorkin (2021), which predicts that total employment in treated local labor markets does not change relative to control local labor markets.

To rationalize the empirical findings on employee earnings, total employment, and recruitment intensity, we build a model in the next section that incorporates recruitment intensity in a classical oligoposny model with wage competition and differentiated jobs.

Figure 6. Difference-in-Differences Analysis: Total Employment

This figure reports the estimates of Equation (3.1) for total employment at the local labor market level. The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.

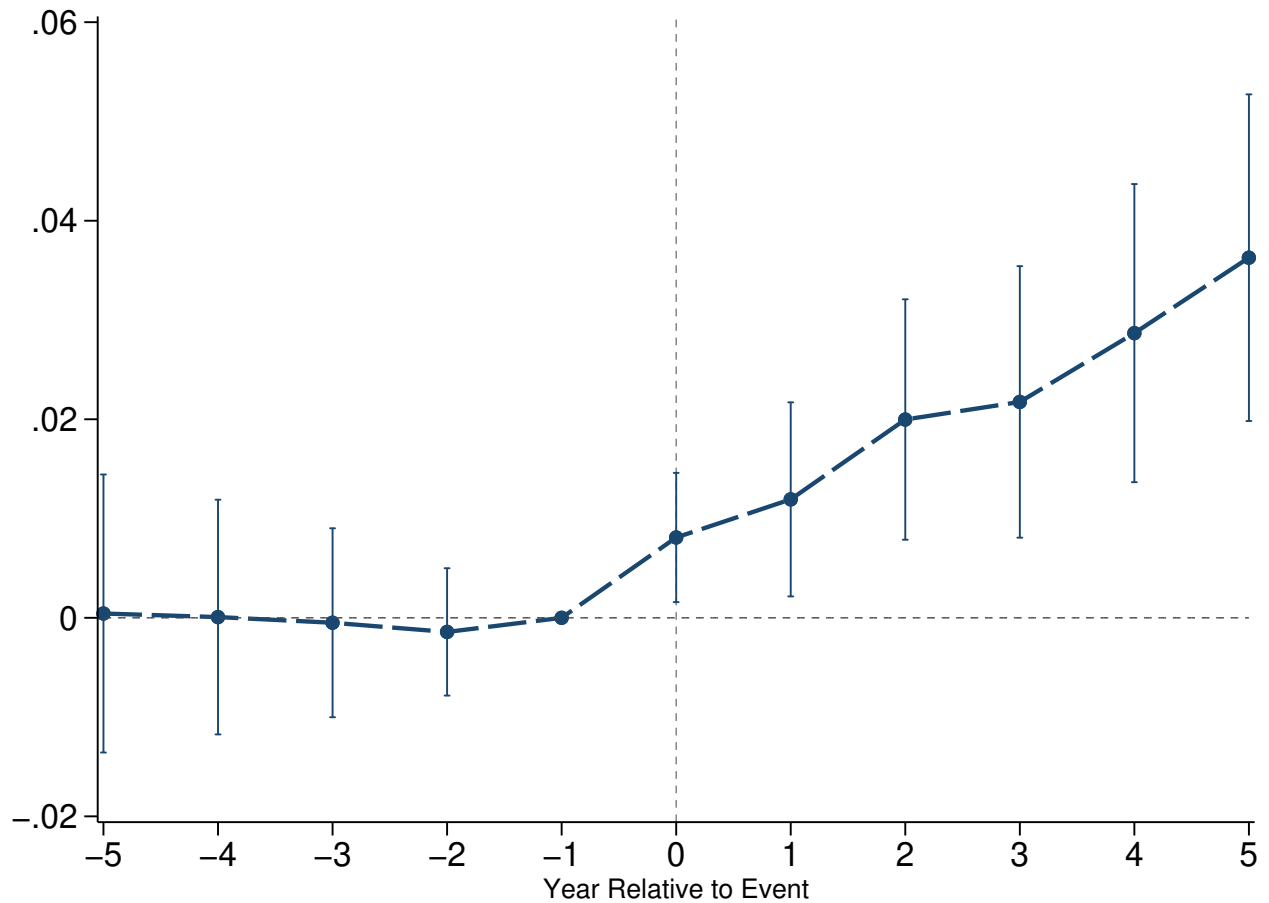
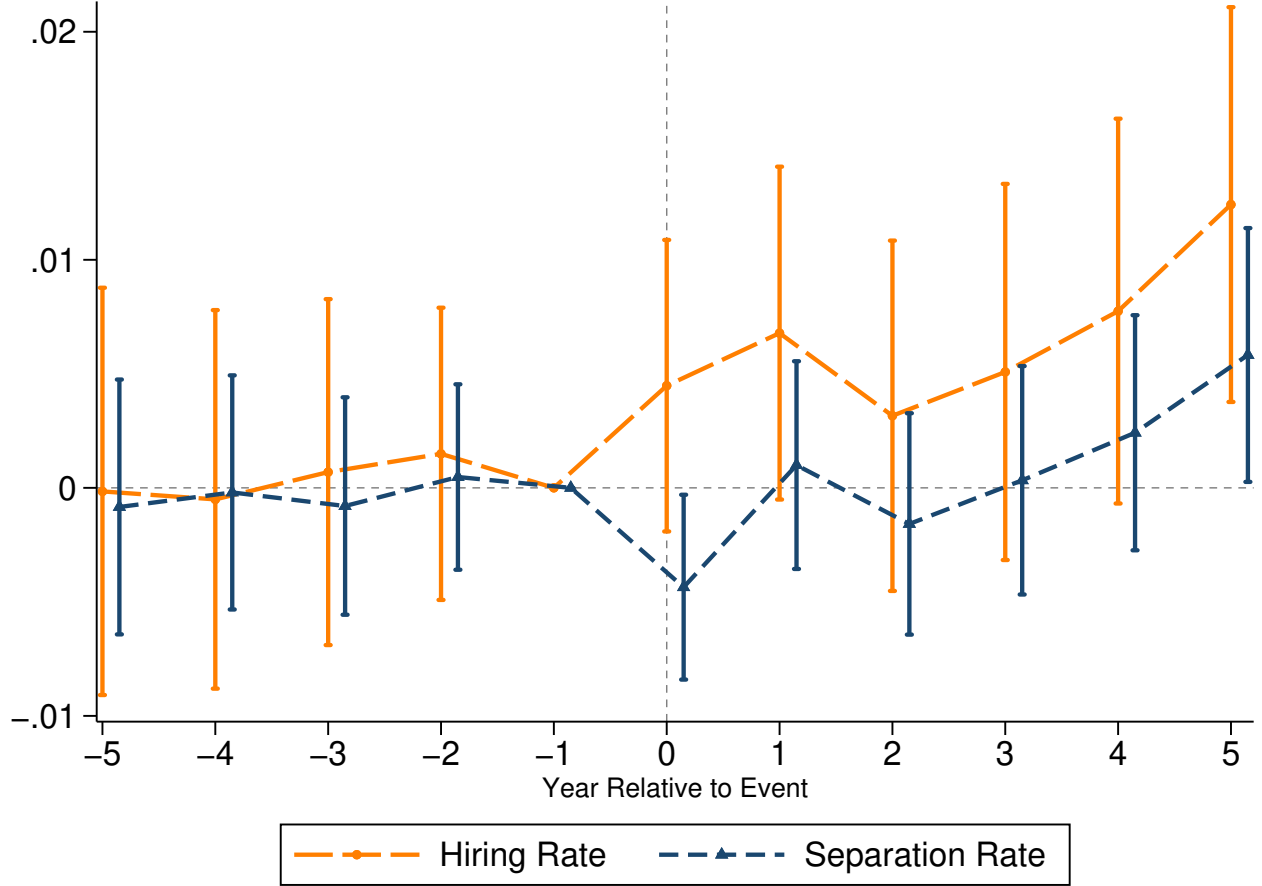


Figure 7. Difference-in-Differences Analysis: Hiring and Separation Rates

This figure reports the estimates of Equation (3.1) for hiring and separation rates at the local labor market level. Hiring rate at the local labor market level are constructed from QWI data. The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.



4 Oligopsony with Common Ownership and Endogenous Recruitment Intensity

In this section, we develop a theoretical model that shows that, when one extends the canonical model of oligopsony with wage competition and differentiated jobs of [Bhaskar, Manning and To \(2002\)](#) to incorporate a recruitment-intensity margin as in [Manning \(2006\)](#), common ownership in a labor market can reduce wages while either increasing or decreasing employment, depending on parameters describing an underlying balance of economic forces. An important difference between our setup and that of [Bhaskar, Manning and To \(2002\)](#) is that they

model differentiated jobs and workers using a [Hotelling \(1929\)](#) linear city model, while we use a multinomial logit random utility model for the labor supply specification, as in [Azar, Berry and Marinescu \(2019\)](#).¹⁶

Consider a labor market with J firms offering differentiated jobs. The market is an oligopsony, with competition in wages and a continuum of workers of mass 1. Worker- i 's utility from working at firm j is,

$$u_{ij} = \alpha \log(w_j) + \epsilon_{ij}, \quad (4.1)$$

where w_j is the wage of firm j 's jobs, and ϵ_{ij} is a worker-firm match-specific shock. We assume that the match-specific shocks are independent and identically distributed, with a Type I extreme value distribution. Higher α expresses a relatively larger role for wages and smaller role for nonwage differences between firms in governing worker utility, making jobs at different firms closer substitutes. This reduces firms' differentiation and market power as employers and is a key parameter in determining whether increased common ownership will increase or decrease employment.

Firms engage in informative advertising of their job openings. We model informative recruiting expenditures similarly to the model of informative product advertising in [Butters \(1977\)](#) and [Hamilton \(2009\)](#). Firm j chooses its recruiting intensity (ϕ_j) given a cost function $a(\phi_j) = -\theta \log(1 - \phi_j)$. Cost is zero when $\phi_j = 0$, goes to infinity as ϕ_j goes to one, and is convex, so that there is an increasing marginal cost of increasing recruiting intensity. When choosing this level of recruiting intensity, a fraction ϕ_j of workers become aware that firm j is hiring.¹⁷ When there are $J - 1$ rival firms, and all other firms have recruiting intensity ϕ_{-j} , the probability that firm j will face a number k of competitors for a given worker, conditional on that worker being aware of firm j , is given by the binomial distribution:

$$p(k; \phi_{-j}, J - 1) = \binom{J - 1}{k} \phi_{-j}^k (1 - \phi_{-j})^{J - 1 - k}. \quad (4.2)$$

The employment share of firm j in the labor market is

$$s_j(w_j, w_{-j}, \phi_j, \phi_{-j}) = \phi_j \sum_{k=0}^{J-1} p(k; \phi_{-j}, J - 1) s_j^{(k)}(w_j; w_{-j}), \quad (4.3)$$

¹⁶ [Azar, Berry and Marinescu \(2019\)](#) estimate a nested logit with heterogeneous firms, while here we use a simple logit with symmetric firms since that is enough for our purposes, which are more illustrative.

¹⁷ [Forsythe and Weinstein \(2021\)](#) show, using firm-level data, that firm-level recruiting expenditures are in fact associated with increased hiring by the firm.

where

$$s_j^{(k)}(w_j; w_{-j}) = \frac{\exp(\alpha \log(w_j))}{\exp[\alpha \log(w_j)] + k \exp[\alpha \log(w_{-j})]}$$

is the market share of firm j among the workers that are informed about firm j and about k rival firms. If there were no recruiting cost ($\theta = 0$), all firms would tell all workers about all openings and there would be no frictional nonemployment. As recruiting costs increase, employer competition weakens and the employment rate can fall. Recruiting cost is the other key parameter (in addition to the wage-sensitivity parameter α) determining how common ownership affects employment.

The employment share of a rival firm in the labor market is

$$s_{-j}(w_j, w_{-j}, \phi_j, \phi_{-j}) = \phi_{-j} \sum_{k=0}^{J-2} p(k; \phi_{-j}, J-2) \left[\phi_j s_{-j}^{(k+1)} + \frac{1 - \phi_j}{k+1} \right], \quad (4.4)$$

where

$$s_{-j}^{(k)}(w_j, w_{-j}) = \frac{\exp(\alpha \log(w_{-j}))}{\exp[\alpha \log(w_j)] + k \exp[\alpha \log(w_{-j})]}$$

is the market share of firm $-j$ among the workers that are informed about firm j and about k rival firms.

The profit of firm j is

$$\pi_j(w_j, w_{-j}, \phi_j, \phi_{-j}) = (A - w_j) s_j(w_j, w_{-j}, \phi_j, \phi_{-j}) - a(\phi_j), \quad (4.5)$$

where A_j is the additional revenue for firm j from hiring another worker, s_j is the labor market share of firm j .

The objective of firm j is to maximize its profit plus a weight λ on profits of the labor market's other firms, expressing the fact that firms may have some common ownership and their shareholders, therefore, partially internalize the profits of rival firms,

$$\zeta_j = (A - w_j) s_j - a(\phi_j) + \lambda \cdot (J - 1) [(A - w_{-j}) s_{-j} - a(\phi_{-j})]. \quad (4.6)$$

The first-order condition for firm j with respect to the wage is,

$$(A - w_j) \frac{\partial s_j}{\partial w_j} + \lambda \cdot \left[(J - 1) (A - w_{-j}) \frac{\partial s_{-j}}{\partial w_j} \right] = s_j, \quad (4.7)$$

where the market share slopes with respect to firm j 's wage are

$$\frac{\partial s_j}{\partial w_j} = \frac{\alpha}{w_j} \phi_j \sum_{k=0}^{J-1} p(k; \phi_{-j}, J-1) s_j^{(k)} (1 - s_j^{(k)}) \quad (4.8)$$

$$\frac{\partial s_{-j}}{\partial w_j} = -\frac{\alpha}{w_j} \phi_{-j} \phi_j \sum_{k=0}^{J-2} p(k; \phi_{-j}, J-2) s_{-j}^{(k+1)} s_j^{(k+1)}. \quad (4.9)$$

The first-order condition for firm j with respect to recruiting effort is,

$$(A - w_j) \frac{\partial s_j}{\partial \phi_j} + \lambda \cdot \left[(J-1) (A - w_{-j}) \frac{\partial s_{-j}}{\partial \phi_j} \right] = \theta / (1 - \phi_j), \quad (4.10)$$

where the market share slopes with respect to firm j 's recruitment intensity are

$$\frac{\partial s_j}{\partial \phi_j} = s_j / \phi_j \quad (4.11)$$

$$\frac{\partial s_{-j}}{\partial \phi_j} = \phi_{-j} \sum_{k=0}^{J-2} p(k; \phi_{-j}, J-2) \left[s_{-j}^{(k+1)} - \frac{1}{k+1} \right]. \quad (4.12)$$

We solve the model numerically by finding the solution to the two nonlinear equations obtained by imposing symmetry (that is, setting $w_j = w_{-j} = w$ and $\phi_j = \phi_{-j} = \phi$) in the first-order conditions).

$$\begin{cases} (A - w) \left\{ \frac{\partial s_j}{\partial w_j} + \lambda (J-1) \frac{\partial s_{-j}}{\partial w_j} \right\} = (1 - (1 - \phi)^J) / J \\ (A - w) \left\{ \frac{\partial s_j}{\partial \phi_j} + \lambda (J-1) \frac{\partial s_{-j}}{\partial \phi_j} \right\} = \theta / (1 - \phi) \end{cases}, \quad (4.13)$$

where all the market share slopes are evaluated at the symmetric wage and recruitment intensity values ($w_j = w_{-j} = w$ and $\phi_j = \phi_{-j} = \phi$):

$$\begin{aligned} \frac{\partial s_j}{\partial w_j} &= \frac{\alpha}{w} \phi \sum_{k=0}^{J-1} p(k; \phi, J-1) \frac{k}{(k+1)^2} \\ \frac{\partial s_{-j}}{\partial w_j} &= -\frac{\alpha}{w} \phi^2 \sum_{k=0}^{J-2} p(k; \phi, J-2) \frac{1}{(k+2)^2} \\ \frac{\partial s_j}{\partial \phi_j} &= \frac{1 - (1 - \phi)^J}{\phi J} \\ \frac{\partial s_{-j}}{\partial \phi_j} &= \phi \sum_{k=0}^{J-2} p(k; \phi, J-2) \left[\frac{1}{k+2} - \frac{1}{k+1} \right] \end{aligned} \quad (4.14)$$

As can be seen in Figure 8, while an increase in common ownership reduces equilibrium wages in all the simulations, whether it decreases or increases equilibrium hiring effort and

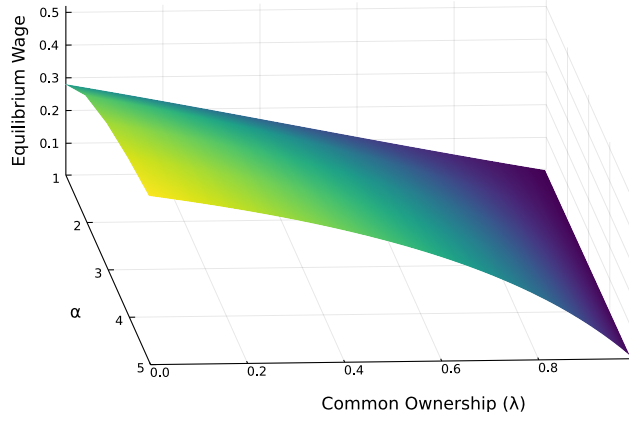
equilibrium employment depends on the other parameters of the model. In this example, common ownership generates an increase in employment when the elasticity parameter α or the cost of recruitment intensity parameter θ are relatively high, and common ownership generates a decrease in employment when α and θ are relatively low.

The intuition for the ambiguous effect of common ownership on employment is the following. Higher common ownership implies internalization of the effects on increased recruiting expenditures on other firms' profits, because some of the extra recruited workers would have otherwise been employed by commonly owned firms. This effect implies that more common ownership would tend to reduce equilibrium recruiting expenditures. However, common ownership also reduces equilibrium wages, increasing the profits per worker that the firms receive. These higher profits per job increase the incentives for firms to expend resources on recruiting more workers in equilibrium. When the latter effect dominates, the net effect of common ownership on equilibrium employment is positive.

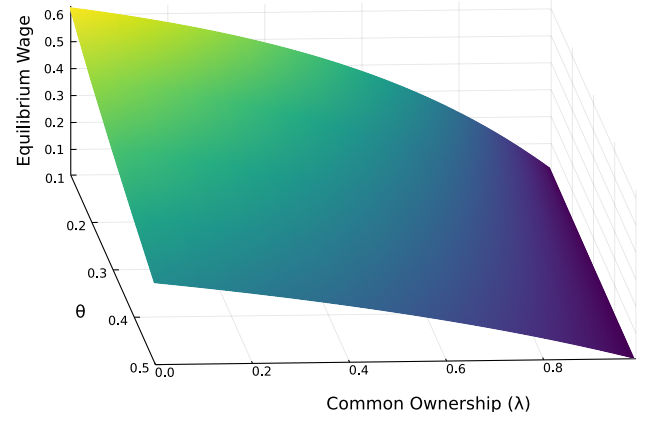
When the wage-sensitivity parameter α is higher, the elasticity of labor supply to the firm with respect to its wage is higher because firms are closer substitutes for one another, and, therefore, equilibrium wages are higher. In this model, higher wages imply less profit per job and less incentive for firms to spend resources on advertising their job openings, which *lowers* equilibrium employment. Common ownership, by reducing equilibrium wages, has the effect of increasing the incentive to spend resources on recruitment.

Figure 8. Theoretical Effect of Common Ownership on Wages, Recruitment Intensity, and Employment

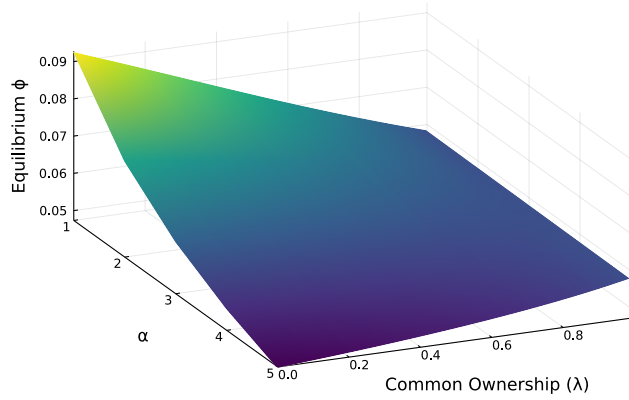
This figure shows the solution to the model for the following parameter values: number of firms $J = 20$, marginal product of labor $A = 1$ (as a normalization), cost of recruitment intensity parameter $\theta = 0.3$ (in the varying α case), and wage sensitivity parameter $\alpha = 3$ (in the varying θ case). The common ownership parameter λ ranges from 0 to 1.



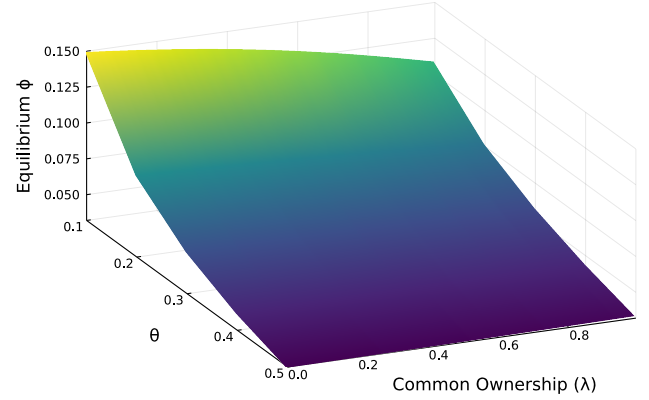
(a) Equilibrium Wage (Varying α)



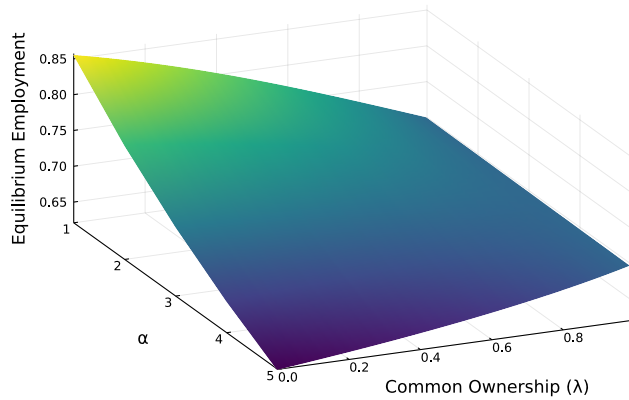
(b) Equilibrium Wage (Varying θ)



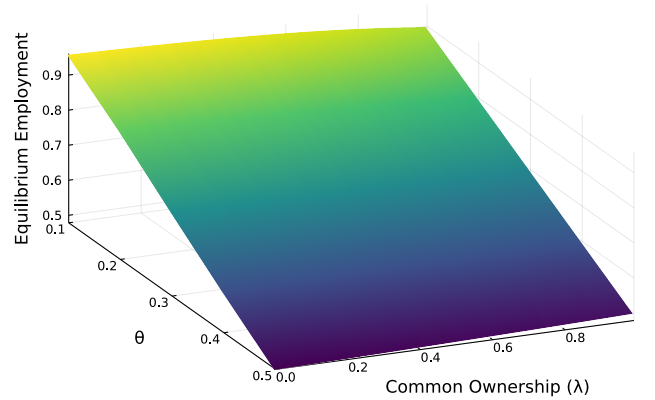
(c) Equilibrium Recruitment Intensity ϕ (Varying α)



(d) Equilibrium Recruitment Intensity ϕ (Varying θ)



(e) Equilibrium Employment (Varying α)



(f) Equilibrium Employment (Varying θ)

5 Conclusion

In this paper, we contribute to the literature on employer market power by measuring common ownership at the local labor market level, and providing the first empirical evidence on the effects of common ownership on employee earnings. We explore natural experiments generated by firms' additions to the S&P 500 index and use a difference-in-differences design to estimate causal effects. Our results suggest that the average annual earnings per employee among nonfocal firms in treated local labor markets are lower compared to the one in control local labor markets after focal firms enter the S&P 500 index. As one would expect, this effect is larger in markets where the ex ante share of S&P 500 firms was higher before the shock.

We also found that the separation rate was higher in treated markets. However, it increases the hiring rate even more, leading to an increase in total employment in treated markets. We show that, while this is inconsistent with existing models of oligopsony or bargaining, it *can* be rationalized through a model of oligopsony with endogenous recruiting intensity.

The policy implications of anticompetitive effects of common ownership in labor markets are complex. Legal scholars have mostly analyzed the antitrust implications of horizontal shareholding in product markets (Elhauge, 2015; Baker, 2015; Posner, Scott Morton and Weyl, 2017; Rock and Rubinfeld, 2020; Posner, 2021), as well as labor market power (Marinescu and Hovenkamp, 2019; Krueger and Posner, 2018; Naidu and Posner, 2021). Evaluating the competitive effects of common ownership in labor markets would require a combination of insights from these two legal literatures. One potential approach would be tackling the issue directly by breaking up large common owners. However, it is important to take into account that there are trade-offs from a social point of view, as low-cost index funds provide substantial cost savings for retail investors compared to more expensive actively managed funds.

It is at least somewhat reassuring that, on average, common ownership in U.S. labor markets is quite low compared to the level in, say, airlines and banks. At the same time, however, common ownership is high in many local industrial labor markets and policymakers should consider how to mitigate the problem.

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Appendix

A Variable Definitions

Variable	Definition
Panel Regression Analyses	
<i>Log(Annual Earnings per Employee)</i>	The natural logarithm of annual earnings per employee in a local labor market. Annual earnings per employee in a local labor market are calculated based on payroll and employment data at the county \times four-digit NAICS level from QCEW. <i>Source:</i> QCEW.
<i>Common Ownership</i>	Average common ownership in a local labor market. It is calculated according to Equation (2.1). <i>Source:</i> Data Axle and institutional ownership data from Backus, Conlon and Sinkinson (2021b) .
<i>Total Institutional Ownership</i>	Average total institutional ownership in a local labor market. It is calculated according to the equation in footnote 5. <i>Source:</i> Data Axle and institutional ownership data from Backus, Conlon and Sinkinson (2021b) .
<i>Top5 Institutional Ownership</i>	Average top5 institutional ownership in a local labor market. It is calculated according to the equation in footnote 5. <i>Source:</i> Data Axle and institutional ownership data from Backus, Conlon and Sinkinson (2021b) .
Difference-in-Differences Analyses	
Outcome Variables	
<i>Log(Annual Earnings per Employee)</i>	The natural logarithm of annual earnings per employee excluding county \times five-digit NAICS cells containing firms entering to the S&P 500 index in a local labor market. <i>Source:</i> QCEW.
<i>Common Ownership</i>	Average common ownership excluding firms entering to the S&P 500 index in a local labor market. It is calculated according to Equation (2.1). <i>Source:</i> Data Axle and institutional ownership data from Backus, Conlon and Sinkinson (2021b) .
<i>Log(Employment)</i>	The natural logarithm of total employment excluding county \times five-digit NAICS cells containing firms entering to the S&P 500 index in a local labor market. <i>Source:</i> QCEW.
local labor market Characteristics	
<i>10th percentile of Log(Estab Emp)</i>	The pretreatment mean of the 10th percentile of the natural logarithm of establishment employment in a local labor market. <i>Source:</i> Data Axle.
<i>25th percentile of Log(Estab Emp)</i>	The pretreatment mean of the 25th percentile of the natural logarithm of establishment employment in a local labor market. <i>Source:</i> Data Axle.

<i>Median percentile of Log(Estab Emp)</i>	The pretreatment mean of the median of the natural logarithm of establishment employment in a local labor market. <i>Source:</i> Data Axle.
<i>75th percentile of Log(Estab Emp)</i>	The pretreatment mean of the 75 percentile of the natural logarithm of establishment employment in a local labor market. <i>Source:</i> Data Axle.
<i>90th percentile of Log(Estab Emp)</i>	The pretreatment mean of the 90 percentile of the natural logarithm of establishment employment in a local labor market. <i>Source:</i> Data Axle.
<i>Share of Public Firms' Emp</i>	The pretreatment mean of employment share of publicly traded firms in a local labor market. <i>Source:</i> Data Axle and CRSP.
<i>Total Institutional Ownership</i>	The pretreatment mean of average total institutional ownership in a local labor market. <i>Source:</i> Data Axle and institutional ownership data from Backus, Conlon and Sinkinson (2021b) .
<i>Top5 Institutional Ownership</i>	The pretreatment mean of average top5 institutional ownership in a local labor market. <i>Source:</i> Data Axle and institutional ownership data from Backus, Conlon and Sinkinson (2021b) .
CZ Characteristics	
<i>Population Density</i>	The pretreatment mean of population density in a CZ. <i>Source:</i> County-level Census Gazetteer files.
<i>Unemployment Rate</i>	The pretreatment mean of unemployment rate in a CZ. <i>Source:</i> County-level data from Local Area Unemployment Statistics (LAUS) program through the Bureau of Labor Statistics (BLS).
<i>% Female</i>	The pretreatment mean of the share of female population in a CZ. <i>Source:</i> Surveillance, Epidemiology, and End Results (SEER) Program.
<i>% White</i>	The pretreatment mean of the share of white population in a CZ. <i>Source:</i> SEER.
<i>% Black</i>	The pretreatment mean of the share of black population in a CZ. <i>Source:</i> SEER.
<i>% Hispanic</i>	The pretreatment mean of the share of Hispanic population in a CZ. <i>Source:</i> SEER.
<i>% Age ≥ 20 & ≤ 44</i>	The pretreatment mean of the share of population with ages between 20 and 44 in a CZ. <i>Source:</i> SEER.
<i>% Age ≥ 45 & ≤ 64</i>	The pretreatment mean of the share of population with ages between 45 and 64 in a CZ. <i>Source:</i> SEER.
<i>% Age ≥ 65</i>	The pretreatment mean of the share of population with ages greater than or equal to 65 in a CZ. <i>Source:</i> SEER.

RTW

The pretreatment mean of the extent to which a CZ is subject to the right-to-work (RTW) law. It is calculated as the average RTW law adoption dummies of all the states in the CZ weighted by the state population share in the CZ (measured in year 2000). *Source:* County-level Census Gazetteer files and [Knepper \(2020\)](#).

NCA Enforcement Index

The pretreatment mean of noncompete agreement (NCA) enforcement level in a CZ. It is calculated as the average NCA enforcement index of all the states in the CZ weighted by the state population share in the CZ (measured in year 2000). *Source:* County-level Census Gazetteer files and [Marx \(Forthcoming\)](#).

B Additional Figures and Tables

Figure A.1. Robustness: Include CZ Fixed Effects

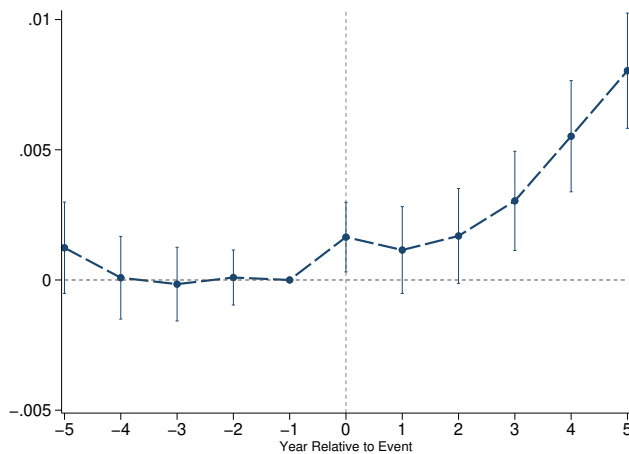
This figure reports the estimates of Equation (3.1) for common ownership and annual earnings per employee at the local labor market level. We include CZ fixed effects when estimating propensity scores. The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.



Figure A.2. Robustness: Thomson Reuters 13F Data

This figure reports the estimates of Equation (3.1) for common ownership and annual earnings per employee at the local labor market level using Thomson Reuters 13F institutional ownership data. The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.

(a) Common Ownership



(b) Log(Annual Earnings per Employee)

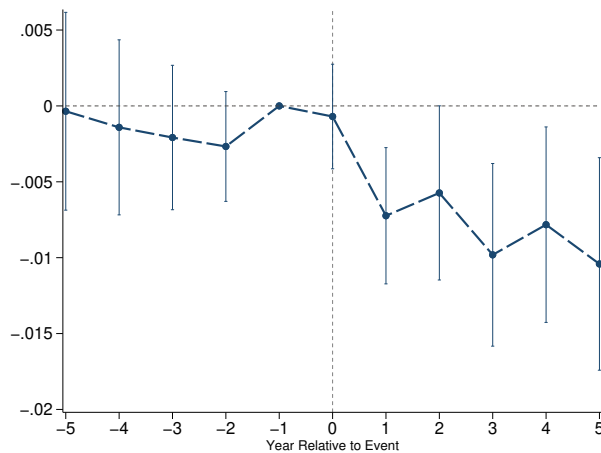
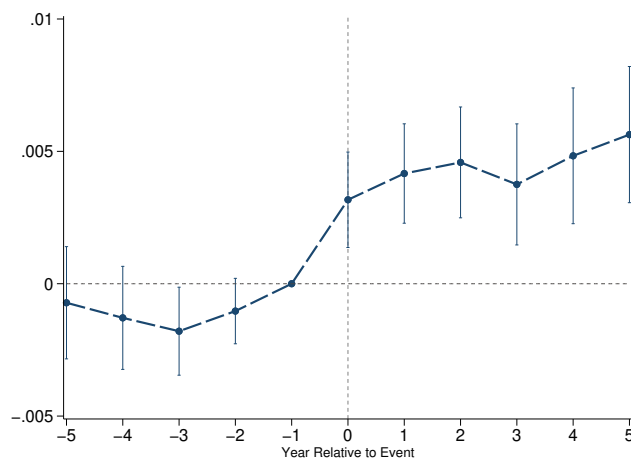


Figure A.3. Robustness: Alternative Definition of a Local Labor Market

This figure reports the estimates of Equation (3.1) for common ownership and annual earnings per employee at the local labor market level using an alternative definition of a local labor market. We define a local labor market as the interaction between a core-based statistical area (CBSA, 2013 version) and a four-digit NAICS industry (2012 version). The bars around point estimates represent 95% confidence intervals and they are based on standard errors clustered at the local labor market level.

(a) Common Ownership



(b) Log(Annual Earnings per Employee)

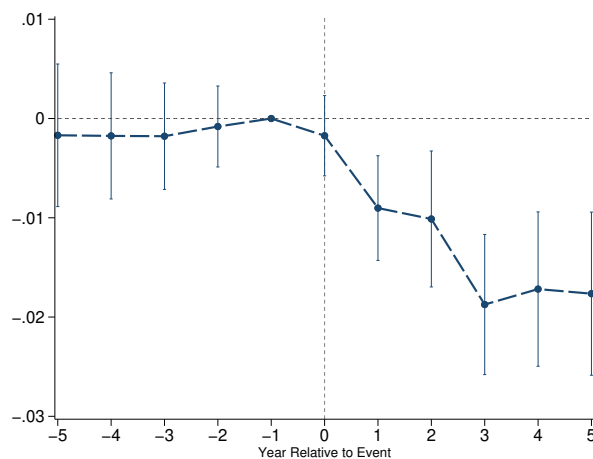


Table A.2. Difference-in-Differences Analysis

This table reports the estimates of Equations (3.1) and (3.2) for common ownership and annual earnings per employee at the local labor market level. In columns (1) and (2), the dependent variable is average common ownership at the local labor market level. In columns (3) and (4), the dependent variable is the natural logarithm of annual earnings per employee at the local labor market level. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated \times Post	0.004*** [0.001]		-0.011*** [0.003]	
Treated \times Year(-5)		0.001 [0.001]		0.000 [0.004]
Treated \times Year(-4)		-0.000 [0.001]		-0.001 [0.003]
Treated \times Year(-3)		-0.001 [0.001]		-0.001 [0.003]
Treated \times Year(-2)		0.000 [0.001]		-0.001 [0.002]
Treated \times Year(0)		0.003*** [0.001]		-0.002 [0.002]
Treated \times Year(+1)		0.004*** [0.001]		-0.008*** [0.002]
Treated \times Year(+2)		0.004*** [0.001]		-0.007** [0.003]
Treated \times Year(+3)		0.003*** [0.001]		-0.013*** [0.003]
Treated \times Year(+4)		0.005*** [0.001]		-0.014*** [0.004]
Treated \times Year(+5)		0.005*** [0.001]		-0.017*** [0.004]
Pair-Local Labor Market FEs	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓
Adjusted R^2	0.588	0.588	0.958	0.958
N	244,431	244,431	244,431	244,431

Table A.3. Heterogeneity by Share of S&P 500 Incumbents

This table reports the estimates of Equations (3.1) and (3.2) for annual earnings per employee at the local labor market level by the share of S&P 500 incumbents in treated local labor markets during the year of an index addition event (*S&P500Share*). Panels A and B report the average and dynamic treatment effects, respectively. Columns (1)–(3) report results for treated local labor markets with low, medium, and higher *S&P500Share*, respectively. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Panel A: Average Treatment Effect			
	Low Share	Medium Share	High Share
	(1)	(2)	(3)
Treated \times Post	0.008 [0.005]	-0.013*** [0.005]	-0.024*** [0.005]
Pair-Local Labor Market FEs	✓	✓	✓
Pair-Year FEs	✓	✓	✓
Adjusted R^2	0.956	0.954	0.958
N	74,756	85,129	84,722
Panel B: Dynamic Treatment Effect			
	Low Share	Medium Share	High Share
	(1)	(2)	(3)
Treated \times Year(-5)	-0.004 [0.006]	0.003 [0.006]	0.007 [0.006]
Treated \times Year(-4)	-0.006 [0.005]	0.003 [0.005]	0.003 [0.005]
Treated \times Year(-3)	-0.004 [0.004]	0.001 [0.004]	0.002 [0.004]
Treated \times Year(-2)	-0.005 [0.003]	0.000 [0.003]	-0.001 [0.003]
Treated \times Year(0)	0.003 [0.003]	-0.003 [0.003]	-0.001 [0.003]
Treated \times Year(+1)	0.004 [0.004]	-0.009** [0.004]	-0.013*** [0.004]
Treated \times Year(+2)	0.007 [0.005]	-0.005 [0.006]	-0.018*** [0.005]
Treated \times Year(+3)	0.003 [0.006]	-0.014*** [0.005]	-0.026*** [0.005]
Treated \times Year(+4)	0.004 [0.006]	-0.016*** [0.006]	-0.024*** [0.006]
Treated \times Year(+5)	0.009 [0.007]	-0.018*** [0.006]	-0.032*** [0.006]
Pair-Local Labor Market FEs	✓	✓	✓
Pair-Year FEs	✓	✓	✓
Adjusted R^2	0.956	0.954	0.958
N	74,756	85,129	84,722

Table A.4. Heterogeneity by Labor Union Power

This table reports the estimates of Equations (3.1) and (3.2) for annual earnings per employee at the local labor market level by pretreatment mean of union coverage rates. Columns (1)—(2) report results for local labor markets with low pretreatment mean of union coverage rates. Columns (3)—(4) report results for local labor markets with high pretreatment mean of union coverage rates. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level..

	Low Union Cov	Low Union Cov	High Union Cov	High Union Cov
	(1)	(2)	(3)	(4)
Treated \times Post	-0.018*** [0.004]		0.004 [0.007]	
Treated \times Year(-5)		0.003 [0.004]		0.002 [0.008]
Treated \times Year(-4)		0.001 [0.004]		-0.004 [0.008]
Treated \times Year(-3)		0.002 [0.003]		-0.011* [0.006]
Treated \times Year(-2)		-0.001 [0.002]		-0.006 [0.005]
Treated \times Year(0)		-0.003 [0.002]		0.002 [0.004]
Treated \times Year(+1)		-0.012*** [0.003]		-0.001 [0.006]
Treated \times Year(+2)		-0.011*** [0.004]		0.003 [0.007]
Treated \times Year(+3)		-0.021*** [0.004]		0.002 [0.007]
Treated \times Year(+4)		-0.022*** [0.004]		0.001 [0.008]
Treated \times Year(+5)		-0.026*** [0.005]		-0.002 [0.009]
Pair-Local Labor Market FEs	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓
Adjusted R^2	0.956	0.956	0.957	0.957
N	129,360	129,360	23,144	23,144

Table A.5. Robustness: Alternative Sets of Matched Treated and Control Local Labor Markets

This table reports the estimates of Equation (3.2) for common ownership and annual earnings per employee at the local labor market level for alternative numbers of matched control local labor markets to a treated local labor market and alternative choices of calipers. Panels A and B report the estimates for common ownership and annual earnings per employee, respectively. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Panel A: Common Ownership					
# of Matched Control Local Labor Markets	10	5	5	15	15
Caliper	N/A	0.1%	N/A	0.1%	N/A
	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.003*** [0.001]	0.003*** [0.001]	0.003*** [0.001]	0.002*** [0.001]	0.003*** [0.001]
Pair-Local Labor Market FEs	✓	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓	✓
Adjusted R^2	0.574	0.566	0.555	0.575	0.562
N	295,482	156,596	161,172	401,929	429,792
Panel B: Employee Earnings					
# of Matched Control Local Labor Markets	10	5	5	15	15
Caliper	N/A	0.1%	N/A	0.1%	N/A
	(1)	(2)	(3)	(4)	(5)
Treated × Post	-0.009*** [0.003]	-0.009*** [0.003]	-0.008*** [0.003]	-0.008*** [0.003]	-0.008*** [0.003]
Pair-Local Labor Market FEs	✓	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓	✓
Adjusted R^2	0.957	0.958	0.957	0.956	0.956
N	295,482	156,596	161,172	401,929	429,792

Table A.6. Robustness: Include CZ Fixed Effects

This table reports the estimates of Equations (3.1) and (3.2) for common ownership and annual earnings per employee at the local labor market level. We include CZ fixed effects when estimating propensity scores. In columns (1) and (2), the dependent variable is common ownership at the local labor market level. In columns (3) and (4), the dependent variable is the natural logarithm of annual earnings per employee at the local labor market level. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated \times Post	0.004*** [0.001]		-0.009*** [0.003]	
Treated \times Year(-5)		0.001 [0.001]		0.001 [0.004]
Treated \times Year(-4)		-0.001 [0.001]		0.001 [0.003]
Treated \times Year(-3)		-0.001 [0.001]		0.002 [0.003]
Treated \times Year(-2)		-0.000 [0.001]		-0.000 [0.002]
Treated \times Year(0)		0.003*** [0.001]		-0.001 [0.002]
Treated \times Year(+1)		0.004*** [0.001]		-0.007** [0.003]
Treated \times Year(+2)		0.004*** [0.001]		-0.004 [0.003]
Treated \times Year(+3)		0.003*** [0.001]		-0.012*** [0.004]
Treated \times Year(+4)		0.005*** [0.001]		-0.011*** [0.004]
Treated \times Year(+5)		0.007*** [0.001]		-0.012*** [0.004]
Pair-Local Labor Market FEs	✓	✓	✓	✓
Pair-Year FEs	✓	✓		✓
Adjusted R^2	0.589	0.589	0.958	0.958
N	215,798	215,798	215,798	215,798

Table A.7. Robustness: Thomson Reuters 13F Data

This table reports the estimates of Equations (3.1) and (3.2) for common ownership and annual earnings per employee at the local labor market level using Thomson Reuters 13F institutional ownership data. In columns (1) and (2), the dependent variable is common ownership at the local labor market level. In columns (3) and (4), the dependent variable is the natural logarithm of annual earnings per employee at the local labor market level. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated \times Post	0.003*** [0.001]		-0.007** [0.003]	
Treated \times Year(-5)		0.001 [0.001]		-0.000 [0.003]
Treated \times Year(-4)		0.000 [0.001]		-0.001 [0.003]
Treated \times Year(-3)		-0.000 [0.001]		-0.002 [0.002]
Treated \times Year(-2)		0.000 [0.001]		-0.003 [0.002]
Treated \times Year(0)		0.002** [0.001]		-0.001 [0.002]
Treated \times Year(+1)		0.001 [0.001]		-0.007*** [0.002]
Treated \times Year(+2)		0.002* [0.001]		-0.006* [0.003]
Treated \times Year(+3)		0.003*** [0.001]		-0.010*** [0.003]
Treated \times Year(+4)		0.006*** [0.001]		-0.008** [0.003]
Treated \times Year(+5)		0.008*** [0.001]		-0.010*** [0.004]
Pair-Local Labor Market FEs	✓	✓	✓	✓
Pair-Year FEs	✓	✓		✓
Adjusted R^2	0.552	0.552	0.957	0.957
N	281,072	281,072	281,072	281,072

Table A.8. Robustness: Alternative Definition of a local labor market

This table reports the estimates of Equations (3.1) and (3.2) for common ownership and annual earnings per employee at the local labor market level using an alternative definition of a local labor market. We define a local labor market as the interaction between a core-based statistical area (CBSA, 2013 version) and a four-digit NAICS industry (2012 version). In columns (1) and (2), the dependent variable is common ownership at the local labor market level. In columns (3) and (4), the dependent variable is the natural logarithm of annual earnings per employee at the local labor market level. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated \times Post	0.005*** [0.001]		-0.013*** [0.003]	
Treated \times Year(-5)		-0.001 [0.001]		-0.002 [0.004]
Treated \times Year(-4)		-0.001 [0.001]		-0.002 [0.003]
Treated \times Year(-3)		-0.002** [0.001]		-0.002 [0.003]
Treated \times Year(-2)		-0.001 [0.001]		-0.001 [0.002]
Treated \times Year(0)		0.003*** [0.001]		-0.002 [0.002]
Treated \times Year(+1)		0.004*** [0.001]		-0.009*** [0.003]
Treated \times Year(+2)		0.005*** [0.001]		-0.010*** [0.003]
Treated \times Year(+3)		0.004*** [0.001]		-0.019*** [0.004]
Treated \times Year(+4)		0.005*** [0.001]		-0.017*** [0.004]
Treated \times Year(+5)		0.006*** [0.001]		-0.018*** [0.004]
Pair-Local Labor Market FEs	✓	✓	✓	✓
Pair-Year FEs	✓	✓		✓
Adjusted R^2	0.580	0.580	0.957	0.957
N	218,130	218,130	218,130	218,130

Table A.9. Difference-in-Differences Analysis: Total Employment

This table reports the estimates of Equations (3.1) and (3.2) for the natural logarithm of total employment at the local labor market level. Columns (1) and (2) report the average and dynamic treatment effects, respectively. Total employment at the local labor market level are constructed from QCEW data. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	Log(Total Emp)	Log(Total Emp)
	(1)	(2)
Treated \times Post	0.023*** [0.007]	
Treated \times Year(-5)		0.000 [0.007]
Treated \times Year(-4)		0.000 [0.006]
Treated \times Year(-3)		-0.000 [0.005]
Treated \times Year(-2)		-0.001 [0.003]
Treated \times Year(0)		0.008** [0.003]
Treated \times Year(+1)		0.012** [0.005]
Treated \times Year(+2)		0.020*** [0.006]
Treated \times Year(+3)		0.022*** [0.007]
Treated \times Year(+4)		0.029*** [0.008]
Treated \times Year(+5)		0.036*** [0.008]
Pair-Local Labor Market FEs	✓	✓
Pair-Year FEs	✓	✓
Adjusted R^2	0.978	0.978
N	244,431	244,431

Table A.10. Difference-in-Differences Analysis: Hiring and Separation Rates

This table reports the estimates of Equations (3.1) and (3.2) for hiring and separation rates at the local labor market level. Columns (1) and (2) report the average and dynamic treatment effects, respectively. Hiring rate at the local labor market level are constructed from QWI data. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	Hiring Rate	Hiring Rate	Separation Rate	Separation Rate
	(1)	(2)	(3)	(4)
Treated \times Post	0.006** [0.003]		0.003 [0.002]	
Treated \times Year(-5)		-0.000 [0.005]		-0.001 [0.003]
Treated \times Year(-4)		-0.001 [0.004]		-0.000 [0.003]
Treated \times Year(-3)		0.001 [0.004]		-0.001 [0.002]
Treated \times Year(-2)		0.001 [0.003]		0.000 [0.002]
Treated \times Year(0)		0.004 [0.003]		-0.004** [0.002]
Treated \times Year(+1)		0.007* [0.004]		0.001 [0.002]
Treated \times Year(+2)		0.003 [0.004]		-0.002 [0.002]
Treated \times Year(+3)		0.005 [0.004]		0.000 [0.003]
Treated \times Year(+4)		0.008* [0.004]		0.002 [0.003]
Treated \times Year(+5)		0.012*** [0.004]		0.006** [0.003]
Pair-Local Labor Market FEs	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓
Adjusted R^2	0.744	0.744	0.790	0.790
N	130,262	130,262	130,262	130,262

C Panel Regressions

In this subsection, we use OLS and 2SLS panel regressions to estimate the relation between common ownership and annual earnings per employee at the local labor market level. Section C.1 introduces empirical specifications, and Section C.2 reports OLS and 2SLS estimation results.

C.1 Empirical Specification

To construct the sample for panel regressions, we merge QCEW data with one-year lagged common ownership and institutional ownership data at the local labor market level. There are 100,332 local labor markets with

707 CZs and 303 four-digit NAICS industries.¹⁸ Dollars are inflated to 2019. Table C.1 reports the summary statistics of the variables in the empirical analysis. Across local labor markets and years, the average annual earnings per employee is \$42,805 and the average employment in a local labor market is 1,276. The average common ownership across local labor market years is 1.4 percentage points. The average local total IO and top five IO are 8.4 and 3.2 percentage points, respectively.

Table C.1. Summary Statistics

This table reports the (unweighted) summary statistics of variables in panel regression analyses. All variables are at the local labor market–year level. Annual earnings per employee is in 2019 dollars.

	N	Mean	Std.Dev.	P10	P50	P90
Annual Earnings per Employee	1,392,835	42,805.253	25,686.284	18,304.795	38,220.980	70,897.578
Employment	1,392,835	1,275.759	5,505.857	21.000	198.000	2,474.000
Common Ownership	1,392,835	0.014	0.067	0.000	0.000	0.026
Total Institutional Ownership	1,392,835	0.084	0.145	0.000	0.005	0.285
Top 5 Institutional Ownership	1,392,835	0.032	0.055	0.000	0.002	0.108

We start with OLS panel regressions and study how changes in common ownership relate to changes in annual earnings per employee in a local labor market by including local labor market and year fixed effects. Specifically, we estimate the following equation:

$$y_{ci,t} = \alpha \lambda_{ci,t-1} + \beta X_{ci,t-1} + \gamma_{ci} + \delta_t + \varepsilon_{ci,t}, \quad (\text{C.1})$$

where c , i , and t index for CZ, four-digit NAICS industry, and year, respectively. $y_{ci,t}$ is the natural logarithm of annual earnings per employee in local labor market (c,i) in year t . $\lambda_{ci,t-1}$ is common ownership in a local labor market ci in year $t-1$. $X_{ci,t-1}$ is a vector of control variables in a local labor market ci measured at year $t-1$. Specifically, we follow [Falato, Kim and von Wachter \(2021\)](#) and control for the average total institutional ownership (IO) and the average ownership of the largest five institutional investors (IO^{Top5}) at the local labor market level. The variable γ_{ci} represents local labor market fixed effects, which helps to control for any time-invariant unobserved characteristics at the local labor market level. The variable δ_t represents year fixed effects, which helps to control for any time-varying shocks at the national level. Unless otherwise stated, observations are unweighted and standard errors are clustered at the local labor market level.

In the first specification, we only include local labor market and year fixed effects. We then further control for the average total and top five institutional ownership in a local labor market. Finally, we run a third specification that further controls for CZ×year fixed effects which absorb any shock at the CZ level in a given year.

Identification assumptions of OLS include a linear functional form, constant treatment effect, and that changes in unobserved characteristics are mean independent of changes in local common ownership conditional on the vector of control variables and fixed effects, that is,

$$E[\varepsilon_{ci,t} | \lambda_{ci,t-1}, X_{ci,t-1}, 1_{ci}, 1_t] = E[\varepsilon_{ci,t} | X_{ci,t-1}, 1_{ci}, 1_t] = 0$$

These identification assumptions of OLS could fail and then our estimates would be biased. However, the direction of bias is not clear ex ante. On one hand, our estimate could be biased downward. For instance, if a local

¹⁸CZ ID=685 (Garfield, MT) and CZ ID=696 (Wrangell-Petersburg, AK) are not in the sample.

labor market experiences a negative shock to labor productivity, then employee earnings would decrease. At the same time, it might induce exits of some privately held firms. This would drive up the measure of local common ownership, resulting in a downward bias of the OLS estimate. On the other hand, our estimate could be biased upward. If a publicly traded firm in a local labor market experiences a shock to firm-specific productivity and decides to acquire some privately held firms in the market. This increased firm-level productivity could drive up both employee earnings and local common ownership simultaneously, resulting in an upward bias of the OLS estimate.

To mitigate the above-mentioned endogeneity concerns, we also use an instrumental variables (IV) strategy and implement it using two-stage least squares (2SLS). The construction of the IV for local common ownership follows [Azar, Marinescu and Steinbaum \(2020\)](#). Specifically, our IV for common ownership in a local labor market in a given year is the average of the equally weighted local common ownership for the same industry in other CZs. Our use of equally weighted average of common ownership ensures that our instrument only uses information on ownership, and no information on endogenous employment shares. The main identification assumption in our IV analysis is that ownership itself is exogenous, which is commonly assumed in the structural common ownership literature (see, for example, [Backus, Conlon and Sinkinson, 2021a](#); [Ruiz-Pérez, 2019](#)).

We again index CZ and four-digit NAICS industry by c and i , respectively, and denote the number of CZs in a year t as N_t . The IV for local common ownership can then be expressed as follows. The IVs for local total institutional ownership and top five institutional ownership are defined analogously.

$$\lambda_{ic,t}^{IV} = \frac{1}{N_t - 1} \sum_{c' \neq c} \lambda_{c'i,t}^{Equally-weighted}$$

This IV purges of any idiosyncratic variation in local common ownership and focuses on the part of variation that is related to nationwide common ownership change. In the labor productivity shock example above, our IV would exclude changes in local common ownership induced by unobserved local shocks in OLS. Studies commonly use this type of leave-this-market-out instrument to deal with endogeneity of local prices ([Nevo, 2001](#)).

However, the estimated results based on this IV strategy should be interpreted carefully. The main threat to the identification of this IV strategy is that, for a given industry, the local shocks driving changes in both employee earnings and local common ownership could be correlated across CZs. For example, suppose that an industry experiences a negative shock that decreases employee earnings across the nation and also leads some privately held firms to exit in some CZs. Mechanically, this shock would induce an increase in the equally weighted version of local common ownership measure in these local labor markets and the exclusion restriction could be violated. As a result, this type of IV cannot protect against industry-level shocks that could affect both firm entry or exit decisions and labor market outcomes at the local labor market level.

C.2 Estimation Results

We report the estimated effects of common ownership on annual earnings per employee in Table [C.2](#). Columns (1)–(3) report OLS estimates. In column (1), we only include local labor market and year fixed effects. The estimated coefficient on *Common Ownership* is -0.04 and is statistically significant at 1 percent level. The estimated effect implies that a one-standard-deviation increase in local common ownership (0.067) is associated with a 0.27 percent ($=0.067 \times -0.04$) decrease in annual earnings per employee. This is \$116 per year given the sample mean of \$42,805. In column (2), we control for average total institutional ownership and average top five institutional ownership at the local labor market level. The result is robust and the estimated coefficient becomes to -0.05 . In

column (3), we further control for CZ×year fixed effects to control for any shock at the CZ level in a year. The result is robust and the estimated coefficient is -0.047 .

Columns (4)–(6) report 2SLS estimates. Across all the columns, the first stage Kleibergen-Paap F-statistic is large, suggesting our instrumental variable is strong. The magnitudes of the estimated common ownership effects are larger than the ones from OLS. Based on the estimates in column (6), our results show that a one-standard-deviation increase in local common ownership is associated with a 1.21 percent ($=0.067 \times 0.181$) decrease in annual wages per employee, or \$518 per year.

Table C.2. Common Ownership and Employee Earnings

This table reports the estimated relation between common ownership and average annual earnings per employee at the local labor market level. Columns (1)–(3) report the results using OLS. Columns (4)–(6) report the results using 2SLS. The instrumental variable for *Common Ownership* is the average of the equally weighted *Common Ownership* for the same industry in all other CZs. The instrumental variables for *Institutional Ownership* and *Top 1 Institutional Ownership* are defined analogously. Standard errors are clustered at the local labor market level. * significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Common Ownership	-0.040*** [0.006]	-0.050*** [0.006]	-0.047*** [0.006]	-0.109*** [0.016]	-0.192*** [0.017]	-0.181*** [0.016]
Total Institutional Ownership		0.011 [0.008]	0.016** [0.008]		0.120*** [0.023]	0.145*** [0.023]
Top5 Institutional Ownership		0.009 [0.019]	-0.014 [0.018]		-0.059 [0.065]	-0.165** [0.065]
Local Labor Market FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓		✓	✓	
CZ×Year FEs			✓			✓
Kleibergen-Paap rk Wald F-stat				5,611.21	1,791.34	1,783.45
Adjusted R ²	0.905	0.905	0.907			
N	1,392,835	1,392,835	1,392,835	1,392,835	1,392,835	1,392,835