COMMON OWNERSHIP IN LABOR MARKETS*

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Abstract

In this paper, we study common ownership in U.S. labor markets, and document that common ownership more than doubled over the period 1999–2017. To identify the causal effects of common ownership on labor market outcomes, we use a firm's addition to the S&P 500 index as a shock to the common ownership of its competitors in local labor markets. 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 decrease relative to the counterfactual. The effect of S&P 500 index additions on employee earnings is stronger in local labor markets where the employment shares of S&P 500 firms were higher or union coverage rates were lower ex ante. The effect is not driven by changes in workforce characteristics. We also find that an increase in common ownership leads to higher separation rates in treated local labor markets. Perhaps surprisingly, it increases their hiring rates even more, resulting in an overall *positive* effect on total employment. While together these facts are inconsistent with the canonical oligopsony model, we show that they *can* be rationalized in a generalized model of oligopsony with a recruitment intensity decision by firms. *JEL* Codes: J42, J31, L40, D40, G34.

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I. Introduction

Ownership of publicly traded U.S. 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 generated a dramatic increase in common ownership of publicly traded firms (see, for example, Azar and Vives, 2021; Backus et al., 2021b).[1] This trend has raised the alarm that a small number of giant asset managers (especially the largest three, 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, forthcoming; 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 et al. (2021b) with data on firms' employment shares in each local labor market, constructed from establishment-level employment data from Data Axle. We find that average common ownership across local labor markets more than doubled in the United States between 1999 and 2017. To measure employee earnings at the local labor market level, we use data from the Quarterly Census of Employment and Wages (QCEW).

To identify the causal effect of common ownership on employee earnings, we follow Boller and Scott Morton (2020) and use natural experiments generated by firms' additions 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. This, in turn, increases overlap between its ownership and that of its publicly traded industry competitors in a local labor market (*nonfocal firms*), especially S&P 500 incumbents. As a result, the average common ownership of nonfocal firms would increase after focal firms are added to the S&P 500 index. Because firm compositions are different across local labor markets before a S&P 500 index addition event, the same event would generate heterogeneous treatment statuses across local labor markets. Based on this variation, we use a difference-in-differences (DiD) design to estimate the causal effect of common ownership on employee earnings.

[1] For earlier contributions that documented the secular rise of common ownership, see also Azar (2012); Fichtner et al. (2017); Azar (2017, 2020).

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

In DiD regressions, we compare changes in employee earnings at nonfocal firms in local labor markets where at least one focal firm enters the S&P 500 index (treated local labor markets) to changes in matched local industries where no firms ever enter or exit the S&P 500 index by the end of estimation window (control local industries).[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 additions.

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 0.4 percentage points during the five-year window after treatment. The magnitude of the estimated effect is economically meaningful and represents a 18 percent increase relative to the sample mean of 2.2 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 the counterfactual during the post-treatment 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 $487 less per year, or $2,437 less in total 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 a different local labor market definition.

The estimated earnings effect of S&P 500 index additions 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 re-implement the matched DiD analysis for each subsample. The estimated effect of S&P 500 index additions is the largest for treated local labor markets in the top tercile of S&P 500 incumbent shares. Annual earnings per employee among nonfocal firms in these treated local labor markets were 2.4 percent lower in the post-treatment period compared to the counterfactual. In comparison, the estimated average treatment effect was only 0.8 percent for treated local labor markets with S&P 500 incumbent shares falling in the bottom tercile.

[3] In a treated local labor market,we also require that there is at least one nonfocal firm that has already been in the S&P 500 index before a shock. To make sure the definition of a treated local labor market to be clean, local labor markets where there are both firms entering and exiting the S&P 500 are excluded from the treatment group.

This heterogeneity result lends further credibility to our DiD estimation strategy. Additional analyses also show that the estimated effect on employee earnings comes from labor markets with low union coverage rates prior to treatment and is not driven by changes in workforce characteristics, suggesting that increased employer market power is more likely to be a driving force behind the employee earnings effect of common ownership.

Our results on employee earnings could be consistent with classical monoposony 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 et al. (2021)—show that changes in employer market power could affect employee earnings without affecting employment levels. However, we find that total employment of nonfocal firms *increases* in treated local labor markets after S&P 500 index additions relative to the counterfactual.

To try to further understand this positive effect on total employment, we examine the effects of common ownership on hiring and separating rates. We find that separation rates increase, consistent with lower wages making the jobs at the treated local labor markets less attractive. However, we also observe an even larger increase in hiring rates in treated local labor markets, which explains (in a proximate way) why employment increases *despite* higher separation rates. This suggests that firms in treated markets are able to and have incentives to increase their employment level—despite having lower wages per employee—by increasing their recruitment 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 (Manning, 2006; Forsythe and Weinstein, 2021).[4] Our model predicts that a higher common ownership among firms in a local labor market would lead to lower equilibrium wages, but its impact on recruitment intensity is ambiguous. On one hand, a higher common ownership could reduce a firm's incentive to spend on recruiting. The reason is that the firm would internalize more of its rivals' profits but an increased recruitment intensity would lead to more competitions and reduce the profits of the firm's competitors. On the other hand, a firm's incentive to recruit could increase when common ownership is higher. This is because a higher common ownership would lead to lower equilibrium wages, resulting in higher profits per recruited employee. It would then incentivize the firm to spend more resources on recruiting. The effect of common ownership on equilibrium recruitment intensity and employment can be positive or negative, depending on the parameters of the model.

[4]One can think of our model as extending the "generalized model of monopsony" of Manning (2006) from a one-firm setting to a multi-firm 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 et al., 2018; Newham et al., 2018; Ruiz-Pérez, 2019; Backus et al., 2021a), executive compensation (Antón et al., 2022), and innovation (López and Vives, 2019; Anton 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 et al., 2010; Manning, 2011; Staiger et al., 2010; Falch, 2010; Ransom and Sims, 2010; Matsudaira, 2013; Goolsbee and Syverson, 2019; Dube et al., 2020; Manning, 2021; Bassier et al., 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 et al., 2020) or employment share (Benmelech et al., 2020; Prager and Schmitt, 2021; Rinz, 2020; Arnold, 2021; Qiu and Sojourner, 2022). 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 et al., 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 rising connections among firms via common shareholders may have increased employer market power in the United States in recent decades.

II. Data Description

II. A. Local Labor Market Definition

We follow Rinz (2020) and define a local labor market as the interaction between a commuting zone (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 in the United States. Another choice of the geographic area in the local 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.

II. B. 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 et al. (2021b).[6] In the United States, all institutional investment managers with at least $100 million

[5]The Data Axle Business Data website is available at https://www.data-axle.com/our-data/business-data/.
[6]The IO data is available at https://sites.google.com/view/msinkinson/research/common-ownership-data.

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 et al. (2021b) scrapes 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 et al. (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 et al. (2021b) with firm's 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 $\lambda_{j,k} = \frac{\sum_{\forall s} \beta_{js}\beta_{ks}}{\sum_{\forall s} \beta_{js}\beta_{js}}$. 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

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

Given that institutional ownership data are at the quarterly level, we first calculate local labor market-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 I 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.

Figure II shows a map of 708 commuting zones in our sample color-coded by the average common ownership in 2017.[7] In each commuting zone, we calculate the employment-weighed average common ownership across four-digit NAICS industries. The map shows that there is a large variation in common ownership across commuting zones. The measured common ownership is higher for commuting zones in the Southern and part of the Midwest region. The commuting zone with the highest common ownership is the one that consists of Benton County, AR, Madison County, AR, Washington County, AR, and McDonald County, MO (CZ

[7] CZ ID=696 (Wrangell-Petersburg, AK) is not in the sample.

ID=240) with a value of 0.205.

Figure III reports the top twenty four-digit NAICS industries in terms of average common ownership in 2017. In each four-digit NAICS industry, we calculate the employment-weighed average common ownership across commuting zones. The top five industries in terms of average common ownership are "Department Stores (NAICS code=4521)", "Other General Merchandise Stores (NAICS code=4529)", "Aerospace Product and Parts Manufacturing (NAICS code=3364)", "Wireless Telecommunications Carriers (except Satellite) (NAICS code=5172)", and "Cable and Other Subscription Programming (NAICS code=5152)".

II. C. 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×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.[8] This procedure produces a measure of total payroll and total employment at the county×2012 version four-digit NAICS industry level that is consistent over time. We aggregate payroll and employment data at the county×4-NAICS level data 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.

III. Difference-in-Differences Analysis

To examine whether and how common ownership affects employee earnings, we explore 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 local competitor firms.[9] Section III. A. introduces the details of research

[8]In 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 2012, 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×2012 NAICS code×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×2012 NAICS code×year cell as the original value times the assigned weight.

[9]Following Boller and Scott Morton (2020) , we do not extend our analysis to the S&P 500 index exits for the following reasons. If a firm exits the S&P 500 index because it goes bankrupt, is acquired, or goes private, we then

design and Section III. B. reports the estimation results.

III. A. Empirical Specification

We follow Boller and Scott Morton (2020) and 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) in a local labor market. Boller and Scott Morton (2020) shows 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. (2022) 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 change 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. 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 9 cohorts in our sample. Combining data on index addition events with data on the locations, employment, and parent firms of establishments in Data Axle, we can measure heterogeneous treatment statuses induced by S&P 500 index additions 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 in a 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

do not have institutional ownership data for this firm after it exits the index. A firm could also exit the S&P 500 index and switch to the S&P 400 index or the S&P 600 index, but Boller and Scott Morton (2020) shows that index switching does not lead to a significant change in institutional ownership.

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 establishment-level earnings data. We use QCEW data to construct annual earnings per employee among nonfocal firms in a local labor market.[10]

A CZ is a cluster of counties but the composition of counties in a CZ×four-digit NAICS with non-missing payroll and employment data in QCEW may change over time. To avoid this composition issue within a local labor market, we therefore focus on county×four-digit NAICS cells with balanced panels of observed QCEW payroll and employment.[11]

For a treated local labor market, we first define focal cells as county×five-digit NAICS cells to which focal firms belong and define nonfocal cells as county×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×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×four-digit NAICS level are clean; they do not contain any information of any focal firm.

For each cohort of S&P 500 index additions, we restrict our sample to county×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×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×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

[10]Data Axle provides information on employment but not payroll at the establishment level.

[11]Census'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.

linear regression in each cohort by regressing a local labor market's treatment status on a list of pre-treatment variables. We then match each treated local labor market to the ten 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 III. B..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 pre-treatment variables used in matching includes the change in local common ownership, the change in the natural logarithm of average annual earnings per employee, and the 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 pre-treatment 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 calculated 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 the enforcement level of noncompete agreement (NCA) in a CZ.

These are measured as follows. Population density at the CZ×year level is defined as population per square mile and is calculated based on the Census Gazetteer files at the county×year level.[12] Unemployment rate at the CZ×year level is calculated based on county×year-level data from Local Area Unemployment Statistics (LAUS) program through the Bureau of Labor Statistics (BLS).[13] Demographics at the CZ×year level are calculated based on county×year-level data from Surveillance, Epidemiology, and End Results (SEER) Program.[14] 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 is from Knepper (2020). To measure the NCA enforcement level in a CZ in a year, we calculate the average NCA en-

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

[13]LAUS data is available at https://www.bls.gov/lau/.

[14]SEER data is available at https://seer.cancer.gov/popdata/download.html.

forcement 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 is 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 I reports the pre-treatment 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×local labor market and matched pair×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).

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

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:

$$y_{p(k)cit} = \beta \times Treated_{p(k)ci} \times \mathbb{1}(t - t_k > 0) + \mu_{p(k)ci} + \eta_{p(k)t} + \epsilon_{p(k)cit}, \qquad \text{(III. .2)}$$

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.

III. B. Estimation Results

III. B..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 (III. .1) for average common ownership of nonfocal firms in a local labor market. The results are reported in Figure IV 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 post-treatment 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% level. Given that the sample average of common ownership of nonfocal firms during the pre-treatment period is 2.2 percentage points, the estimated average treatment effect is economically meaningful and represents an 18% 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 (III. .1) for average annual earnings per employee among nonfocal firms in a local labor market. The results are in Figure V and columns (3) and (4) of Table A.2. The estimated coefficients during the pre-treatment period are close to zero and statistically insignificant, adding credibility to the maintained parallel trends assumption post-treatment. 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% relative to control local labor markets after focal firms enter the S&P 500 index, and it is statistically significant at 1% level. Given that the average nonfocal firms' annual earnings per employee in treated local labor markets during the pre-treatment 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 V 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% 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%.

III. B..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 re-implement the procedure described in Section III. A. and match it to a set of control local labor markets. We then re-estimation equation (III. .1) for each subsample and report the results in Figure VI 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% lower compared to the counterfactual. In contrast, for treated local labor markets with *S&P500Share* falling in the bottom tercile, the estimated coefficient on Treated$\times$Post is 0.8 percentage points and is statistically insignificant. The difference between these two estimates is statistically significant at the 1% level. This heterogeneity result lends further credibility to our DiD strategy.

III. B..3 Robustness

In this subsection, we perform five 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 fifteen control local labor markets with the closest propensity scores. We set the caliper at 0.1% 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 five control local labor markets with the closest propensity scores. We set the caliper at 0.1% 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 pre-treatment 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 increase 0.4 percentage points while employee earnings is 0.9% 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 re-estimate equation (III. .1). These data are from the Wharton Research Data Services (WRDS) and we correct the errors in 13F data using the methods in Ben-David et al. (2021). We use data between 1997 and 2018 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 re-implement the procedure described in Section III. A.. 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 market 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 et al., 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 et al., 2021a; Ruiz-Pérez, 2019). This IV purges 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$\times$year fixed effects, OLS estimates suggest that a one-standard-deviation increase in local common ownership is associated with a 0.31% decrease in annual earnings per employee, while IV estimates imply a one-standard-deviation increase in common ownership reduces employee earnings by 1.21%, or $518 per year. As in Azar et al. (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 the Appendix.

III. C. 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).[15] 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 (UI) 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×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. Since QWI does not report statistics below the county×4-digit NAICS level, 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 Hispanic workers. We then merge these measures with the sample used in Figure V. Panel A of Table II 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 anlaysis estimates that S&P 500 index additions lead to a 0.5 percentage points 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 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 non-white workers. Our estimates show that S&P 500 index additions increase

[15] QWI data is available at https://ledextract.ces.census.gov/static/data.html.

the shares of young, female, and non-white workers by 0.6, 0.3 and 0.3 percentage points, respectively. Given that young, female, and non-white 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 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 (III. .2). The results are reported in Panel B of Table II. 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 Treated×Post is -0.009 and statistically significant at 1% 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:

$$y_{p(k)cit} = \beta^{treated,pre} \times X_{p(k)cit} + \mu_{p(k)ci} + \eta_t + \epsilon_{p(k)cit}, \tag{III. .3}$$

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

$$y_{p(k)cit} = \beta^{control,pre} \times X_{p(k)cit} + \mu_{p(k)ci} + \eta_{p(k)t} + \epsilon_{p(k)cit}, \tag{III. .4}$$

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, non-white, 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 below:

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

Table III reports the results. Panel A reports the estimated marginal effects of workforce characteristics on the natural logarithm of employee earnings using pre-treatment 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 non-white 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% (=(0.354+0.093+0.106-0.256-0.182)/1.1) of the changes in employee earnings after S&P 500 index additions.

III. D. Heterogeneity Effects by Labor Union Power

In this subsection, we examine whether and how labor union power affects the impacts of S&P 500 index additions on employee earnings. If the employee earnings effect of S&P 500 index additions is driven by increases in employers' market power, then stronger labor union power in a local labor market could act as a countervailing force and the estimated effect on employee earnings is expected to be larger in local labor markets with lower union power before S&P 500 index additions.

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.[16] 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 of S&P 500 index additions, we split local labor markets into ones with high and low labor union power based on the median of pre-treatment mean of union coverage rates and estimate equations (III. .1) and (III. .2) for local labor markets with high and low pre-treatment union coverage rates separately. We report the results in Figure VII and Table A.4.

[16]The 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 is not available in CPS.

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% 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% level.

III. E. 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 and the effect comes from local labor markets with low union coverage rates prior to treatment. This suggests that increased 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 maximizes 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 effect operates 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 et al. (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 re-encounter 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 (III. .1) by replacing the dependent variable as the natural logarithm

of total employment. The results are reported in Figure VIII 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 post-treatment period, nonfocal firms' total employment in treated local labor markets increases by 2.3% relative to the counterfactual.[17]

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 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, we winsorize them at the 99 percentile to mitigate the effects of outliers.

We then repeat the estimation procedure in Section III. A. and additionally match on the changes in hiring and separation rates during pre-treatment period. The results are reported in Figure IX and Table A.10. The results first show that separation rates in treated local labor markets gradually increase relative to that in control local labor markets after S&P 500 index additions. By the end of fifth year after treatment, separation rates in treated local labor markets increase 0.7 percentage points relative to the counterfactual, representing a 1.3% increase relative to the average separation rate in treated local labor markets one year prior to treatment (53.7 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 IX further show that hiring rates of treated local labor markets increase even more after S&P 500 index additions. The estimates show that hiring rates of treated local labor markets increase 2.1 percentage points relative to the counterfactual by the end of fifth year after treatment, representing a 3.0% increase relative to the average hiring rate in treated local labor markets one year prior to treatment (69.4 percentage points).

[17] Given 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.

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 et al. (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 hiring rates, we build a model in the next section that incorporates recruitment intensity in a classical oligoposny model with wage competition and differentiated jobs.

IV. Oligopsony with Common Ownership and Endogenous Recruitment Intensity

There are at least two popular models of employer market power in the literature. The first one is the classical model of oligopsony with an upward-sloping labor supply curve. In this model, employee earnings and employment are tightly connected and the model predicts that a decline in wages necessarily implies a decline in employment. The second model is based on the canonical search and bargain model as in Jarosch et al. (2021). In this model, an increase in employer market power would reduce employee earnings without affecting the level of employment. The theoretical predictions from these two models are at odds with our empirical findings that common ownership reduces employee earnings but increases total employment in a local labor market.

In this section, we develop a theoretical model that can rationalize our empirical findings. Specifically, we extend the classical model of oligopsony in two directions: (i) it has differentiated jobs and wage competition, as in Bhaskar et al. (2002), and (ii) it incorporates a recruitment-intensity margin as in Manning (2006). With these additional features, our model shows that a higher common ownership in a labor market could lead to lower wages and a higher total employment in equilibrium.[18]

Let's consider a labor market with J firms offering differentiated jobs. The market is an oligopsony and firms compete in wages. There is a continuum of workers of mass 1. Worker-

[18] An important difference between our setup and that of Bhaskar et al. (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.

i's utility from working at firm j is,

$$u_{ij} = \alpha \log(w_j) + \epsilon_{ij}, \tag{IV. .1}$$

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. A higher α expresses a relatively more significant role for wages and a more minor role for non-wage job attributes between firms in governing worker utility, making jobs at different firms closer substitutes. This reduces firms' differentiation in jobs and market power as employers. α is a key parameter that determines the impact of common ownership on total 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). A worker observes the job posting of firm j with probability ϕ_j. Among all the job postings that the worker observes, she chooses the one that offers the highest utility. It is possible that the worker observes zero job postings. Therefore, there can be frictional unemployment for this reason, even there is no outside option in the model.[19] Firm j chooses its recruitment intensity ϕ_j given a cost function $a(\phi_j) = -\theta \log(1 - \phi_j)$. Recruitment cost is zero when $\phi_j = 0$, and approaches to infinity as ϕ_j is close to one. $a(\phi_j)$ is convex, so that there is an increasing marginal cost of increasing recruitment intensity.[20] Manning (2006) provides evidence supporting this assumption. If there were no recruiting costs ($\theta = 0$), all firms would advertise job postings to all workers and there would be no frictional unemployment. As recruiting cost increases, employer competition would weaken and the employment rate could fall as a consequece.

We will focus on finding symmetric equilibria. For this purpose, it is useful to calculate the probability that firm j faces k rivals for a given worker who is informed about its job posting, when each of its symmetric rival sets its recruitment intensity to ϕ_{-j}. When there are $J-1$ rival firms, such a probability is given by the binomial distribution:

$$p(k; \phi_{-j}, J-1) = \binom{J-1}{k} \phi_{-j}^k (1 - \phi_{-j})^{J-1-k}. \tag{IV. .2}$$

For a given set of chosen wages and recruitment intensities by firm j and each of its rival, $\{w_j, w_{-j}, \phi_j, \phi_{-j}\}$, the employment share of firm j among all potential workers in the labor

[19] It would be possible to add an outside option to our model, corresponding to out of the labor force, but it is not essential to the point we want to make.

[20] Forsythe and Weinstein (2021) shows that firm-level recruiting expenditures are indeed associated with increased hiring by the firm.

market (including the unemployed) is given by

$$s_j(w_j, w_{-j}, \phi_j, \phi_{-j}) = \phi_j \sum_{k=0}^{J-1} p(k; \phi_{-j}, J-1) s_j^{(k)}(w_j; w_{-j}), \tag{IV. .3}$$

where

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

is the market share of firm j among the workers that are informed about the job postings of firm j and its k rivals.

The intuition of equation (IV. .2) is the following. When firm j sets its recruitment intensity to be ϕ_j, a measure of workers of that size are informed about its job posting. Among these ϕ_j workers, $p(k; \phi_{-j}, J-1)$ of them also observe the job postings of firm j's k rivals. Among the workers that observe k rivals' job postings, firm j's market share is given by the multinomial logit market share $s_j^{(k)}(w_j; w_{-j})$.

The employment share of a firm j's rival among all potential workers in the labor market is given by

$$s_{-j}(w_j, w_{-j}, \phi_j, \phi_{-j}) = \phi_{-j} \sum_{k=0}^{J-2} p(k; \phi_{-j}, J-2) \left[\phi_j s_{-j}^{(k+1)} + \frac{1-\phi_j}{k+1}\right], \tag{IV. .4}$$

where

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

is the market share of firm $-j$ among the workers that are informed about the job postings of firm j and firm $-j$'s k rivals. There are two terms in the bracket in equation (IV. .4) and the interpretation is the following. With a probability of ϕ_j, a worker that is informed about the job postings of firm $-j$ and its k rivals could also observe firm j's job posting. In this case, firm $-j$'s market share is given by $s_{-j}^{(k)}(w_j, w_{-j})$; with a probability of $1-\phi_j$, a worker that is informed about the job postings of firm $-j$ and its k rivals does not observe firm j's job posting. In this case, firm $-j$'s market share is simply $1/(k+1)$.

For a given set of chosen wages and recruitment intensities by firm j and each of its rival, $\{w_j, w_{-j}, \phi_j, \phi_{-j}\}$, the profit of firm j is given by

$$\pi_j(w_j, w_{-j}, \phi_j, \phi_{-j}) = (A - w_j) s_j(w_j, w_{-j}, \phi_j, \phi_{-j}) - a(\phi_j), \tag{IV. .5}$$

where A is the additional revenue for firm j from hiring another worker, which we assume is symmetric across firms.

When there is common ownership in the labor market, that is, firms are connected via com-

mon owners, firm j would partially internalize the profits of its rivals. We incorporate this idea into our model by assuming that firm j chooses its wages, w_j, and recruitment intenstiy, ϕ_j, to maximize its profit plus a weight λ times the profits of its rivals in the labor market, taking the choices of $\{w_{-j}, \phi_{-j}\}$ by its rivals as given:

$$\max_{w_j,\phi_j} \left(A - w_j\right) s_j(w_j, w_{-j}, \phi_j, \phi_{-j}) - a(\phi_j) + \lambda \cdot (J-1) \left[\left(A - w_{-j}\right) s_{-j}(w_j, w_{-j}, \phi_j, \phi_{-j}) - a(\phi_{-j})\right]. \tag{IV. .6}$$

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

$$-s_j + (A - w_j)\frac{\partial s_j}{\partial w_j} + \lambda \cdot \left[(J-1)\left(A - w_{-j}\right)\frac{\partial s_{-j}}{\partial w_j}\right] = 0, \tag{IV. .7}$$

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

$$\frac{\partial s_j}{\partial w_j} = \frac{\alpha}{w_j}\phi_j \sum_{k=0}^{J-1} p(k; \phi_{-j}, J-1) s_j^{(k)}(1 - s_j^{(k)}) \tag{IV. .8}$$

$$\frac{\partial s_{-j}}{\partial w_j} = -\frac{\alpha}{w_j}\phi_{-j}\phi_j \sum_{k=0}^{J-2} p(k; \phi_{-j}, J-2) s_{-j}^{(k+1)} s_j^{(k+1)}. \tag{IV. .9}$$

Intuitively, an increase in its wages by one dollar has two opposing effects on firm j's profits. On one hand, it reduces its profits per worker by one dollar, and this reduces overall profits by its market share s_j. This is captured in the first term of equation (IV. .7). On the other hand, increasing wages would increase firm j's market share by $\frac{\partial s_j}{\partial w_j}$, and this increases its profits because the margin $A - w_j$ is applied to more workers. This is captured in the second term of equation (IV. .7). With common ownership, firm j internalizes the fact that some of this increase in its market share comes at the expense of its rivals, whose profits firm j internalizes at a rate λ. This is what drives the third term of equation (IV. .7). This last term, *ceteris paribus*, implies that an increase in common ownership reduces firm j's incentive to increase wages.

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

$$(A - w_j)\frac{\partial s_j}{\partial \phi_j} - \theta/(1 - \phi_j) + \lambda \cdot \left[(J-1)\left(A - w_{-j}\right)\frac{\partial s_{-j}}{\partial \phi_j}\right] = 0, \tag{IV. .10}$$

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

$$\frac{\partial s_j}{\partial \phi_j} = s_j/\phi_j \tag{IV. .11}$$

$$\frac{\partial s_{-j}}{\partial \phi_j} = \phi_{-j} \sum_{k=0}^{J-2} p(k; \phi_{-j}, J-2) \left[s_{-j}^{(k+1)} - \frac{1}{k+1} \right]. \tag{IV. .12}$$

The intuition is as follows. Increasing its recruitment intensity has opposing effects on firm j's profits. An increase in its recruitment intensity would increase firm j's market share by $\frac{\partial s_j}{\partial \phi_j}$, and this increases profits because the margin $A - w_j$ is applied to more workers. This is captured in the first term of equation (IV. .10). But increasing recruitment intensity is costly and the marginal cost is reflected in the second term of equation (IV. .10).

Common ownership makes firm j internalize the fact that, when it increases recruitment intensity, some of its increase in market share comes at the expense of its rivals. As in the first-order condition for wages (equation (IV. .7)), firm j internalizes its rivals' profits at a rate λ. This is captured by the third term of equation (IV. .10). *Ceteris paribus*, this would imply that higher common ownership would reduce firm j's incentive to increase recruitment intensity. However, if common ownership drives down wages in equilibrium, then it increases the first term of equation (IV. .10), implying that each additional worker that firm j hires is more profitable. This would increase firm j's incentive to increase its recruitment intensity. These two conflicting economic forces are the reason why, as we will see in the numerical simulations, the effect of common ownership on employment could be positive or negative, depending on the parameters.

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

$$\begin{cases} (A-w)\left\{ \frac{\partial s_j}{\partial w_j} + \lambda(J-1)\frac{\partial s_{-j}}{\partial w_j} \right\} = (1-(1-\phi)^J)/J \\ (A-w)\left\{ \frac{\partial s_j}{\partial \phi_j} + \lambda(J-1)\frac{\partial s_{-j}}{\partial \phi_j} \right\} = \theta/(1-\phi) \end{cases}, \tag{IV. .13}$$

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

$$\begin{array}{l} \frac{\partial s_j}{\partial w_j} = \frac{\alpha}{w}\phi \sum_{k=0}^{J-1} p(k; \phi, J-1) \frac{k}{(k+1)^2} \\ \frac{\partial s_{-j}}{\partial w_j} = -\frac{\alpha}{w}\phi^2 \sum_{k=0}^{J-2} p(k; \phi, J-2) \frac{1}{(k+2)^2} \\ \frac{\partial s_j}{\partial \phi_j} = \frac{1-(1-\phi)^J}{\phi J} \\ \frac{\partial s_{-j}}{\partial \phi_j} = \phi \sum_{k=0}^{J-2} p(k; \phi, J-2) \left[\frac{1}{k+2} - \frac{1}{k+1} \right] \end{array}. \tag{IV. .14}$$

In equilibrium, the total employment in a labor market is equal to $1-(1-\phi)^J$. There-

fore, the effect of common ownership on recruitment intensity and total employment would be qualitatively the same.

We set the number of firm J to be 20 and marginal product of labor A to be 1 (as a normalization) when solving the model. We report the results in Figure X. In the left panel, we examine how the impacts of common ownership on wages, recruitment intensity, and employment vary with the wage sensitivity parameter α. In this panel, we set the cost of recruitment intensity θ=0.3. In the right panel, we examine how the impacts of common ownership on wages, recruitment intensity, and employment vary with θ that governs recruiting cost. In this panel, we set the wage sensitivity parameter α=3.

As can be seen in Figure X, an increase in common ownership always reduces equilibrium wages but its impact on recruitment intensity or total employment depends on α or θ. In this example, common ownership generates an increase in employment when the wage sensitivity parameter α or the cost of recruitment intensity parameter θ is relatively high, and common ownership generates a decrease in employment when α or θ is relatively low.

As we discussed earlier, the intuition for the ambiguous effect of common ownership on employment is the following. A higher common ownership implies that a firm would internalize more the effect of an increased recruitment intensity on its rivals' profits, because some of the extra recruited workers could have otherwise been employed by firms that share common owners. This effect implies that a higher common ownership would tend to reduce equilibrium recruitment intensity. However, a higher common ownership also reduces equilibrium wages, increasing the profits per worker that the firms receive. These higher profits per job *increase* a firm's incentive to recruit more workers in equilibrium, at least when these workers are more likely to be recruited from the unemployed. When the later "profit-per-worker" effect dominates, the net effect of common ownership on equilibrium employment could be positive.

The positive effect of common ownership on employment is more likely to happen when equilibrium employment is lower without common ownership, because then recruited workers are more likely not coming from rival firms. A higher wage-sensitivity parameter α implies that firms are closer substitutes, resulting in higher equilibrium wages. In this model, higher wages imply that profits per worker are lower and a firm has less incentive to spend resources on advertising their job openings. As a result, equilibrium employment would be *lower* when there is no common ownership. Similarly, when the recruitment cost parameter θ is higher, a firm has less incentive to spend on recruitment, leading to a *lower* equilibrium employment when common ownership is zero. Therefore, when α or θ is higher, a higher common ownership could increase a firm's incentive to spend resources on recruitment because newly recruited workers more likely come from the unemployed and it comes less at the expense of its rival firms.

V. 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 local labor market outcomes. 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 counterfactual after focal firms enter the S&P 500 index. As one would expect, this effect is larger in markets where the ex ante employment shares of S&P 500 firms were higher. Further analyses show that the effect comes from local labor markets with low union coverage rates prior to treatment and is not driven by changes in workforce characteristics after S&P 500 index additions.

We also find that S&P 500 index additions lead to an increase in total employment in treated local labor markets. Such an effect is driven by an increase in hiring rates relative to separation rates. We show that, while this is inconsistent with existing models of employer market power, it *can* be rationalized through a model of oligopsony with endogenous recruitment 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 et al., 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 will require a combination of insights from these two 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 substantial 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.

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APPENDIX

A. 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 A. A. introduces empirical specifications and Section A. B. reports OLS and 2SLS estimation results.

A. A. 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.[21] Dollars are inflated to 2019. Table A.11 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.

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:

$$y_{ci,t} = \alpha\lambda_{ci,t-1} + \beta X_{ci,t-1} + \gamma_{ci} + \delta_t + \varepsilon_{ci,t}, \tag{A.1}$$

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 et al. (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

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

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 5 institutional ownership in a local labor market. Finally, we run a third specification that further controls for CZ$\times$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 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 private-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 et al. (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 et al., 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 nation-wide 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 endogeniety 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.

A. B. Estimation Results

We report the estimated effects of common ownership on annual earnings per employee in Table A.12. 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% level. The estimated effect implies that a one-standard-deviation increase in local common ownership (0.067) is associated with a 0.27% (=0.067*-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 owner-

ship is associated with a 1.21% (=0.067*-0.181) decrease in annual wages per employee, or $518 per year.

REFERENCES

Abowd, John M., Bryce E. Stephens, Lars Vilhuber, Fredrik Andersson, Kevin L. McKinney, Marc Roemer, and Simon Woodcock (2009) "The LEHD Infrastructure Files and the Creation of the Quarterly Workforce Indicators.," *In Producer Dynamics. , ed. Timothy Dunne, J. Bradford Jensen and Mark J. Roberts*, p. 149–234.

Anton, Miguel, Florian Ederer, Mireia Giné, and Martin C Schmalz (2021) "Innovation: the bright side of common ownership?" *Available at SSRN 3099578*.

Antón, Miguel, Florian Ederer, Mireia Giné, and Martin C Schmalz (2022) "Common ownership, competition, and top management incentives," *Ross School of Business Paper*.

Arnold, David (2021) "Mergers and Acquisitions, Local Labor Market Concentration, and Worker Outcomes," *Working Paper*.

Ashenfelter, Orley C., Henry Farber, and Michael R. Ransom (2010) "Labor market monopsony," *Journal of Labor Economics*, Vol. 28, pp. 203–210, URL: http://www.jstor.org/stable/10.1086/653654.

Azar, José (2012) "A new look at oligopoly: Implicit collusion through portfolio diversification," *Ph.D. Thesis, Princeton University*.

——— (2017) "Portfolio diversification, market power, and the theory of the firm," *Market Power, and the Theory of the Firm (August 23, 2017)*.

——— (2020) "The common ownership trilemma," *The University of Chicago Law Review*, Vol. 87, pp. 263–296.

Azar, José, Steven Berry, and Ioana Elena Marinescu (2019) "Estimating labor market power," *Available at SSRN 3456277*.

Azar, José, Ioana Marinescu, and Marshall Steinbaum (2020) "Labor market concentration," *Journal of Human Resources*, pp. 1218–9914R1.

Azar, José, Martin C. Schmalz, and Isabel Tecu (2018) "Anticompetitive Effects of Common Ownership," *Journal of Finance*, Vol. 73, pp. 1513–1565.

Azar, José and Xavier Vives (2021) "General Equilibrium Oligopoly and Ownership Structure," *Econometrica*, Vol. 89, pp. 999–1048.

Backus, Matthew, Christopher Conlon, and Michael Sinkinson (2021a) "Common ownership and competition in the ready-to-eat cereal industry,"Technical report, National Bureau of Economic Research.

——— (2021b) "Common ownership in America: 1980–2017," *American Economic Journal: Microeconomics*, Vol. 13, pp. 273–308.

Baker, Jonathan B (2015) "Overlapping financial investor ownership, market power, and antitrust enforcement: My qualified agreement with Professor Elhauge," *Harv. L. Rev. F.*, Vol. 129, p. 212.

Bassier, Ihsaan, Arindrajit Dube, and Suresh Naidu (2022) "Monopsony in Movers The Elasticity of Labor Supply to Firm Wage Policies," *Journal of Human Resources*, Vol. 57, pp. S50–s86.

Ben-David, Itzhak, Francesco Franzoni, Rabih Moussawi, and John Sedunov (2021) "The Granular Nature of Large Institutional Investors," *Management Science*, Vol. 67, pp. 6629–6659.

Benmelech, Efraim, Nittai K Bergman, and Hyunseob Kim (2020) "Strong employers and weak employees: How does employer concentration affect wages?" *Journal of Human Resources*, pp. 0119–10007R1.

Bhaskar, Venkataraman, Alan Manning, and Ted To (2002) "Oligopsony and monopsonistic competition in labor markets," *Journal of Economic Perspectives*, Vol. 16, pp. 155–174.

Bivens, Josh and Lawrence Mishel (2015) "Understanding the historic divergence between productivity and a typical worker's pay: Why it matters and why it's real," *Economic Policy Institute. https://www. epi. org/files/2015/understanding-productivity-pay-divergence-final. pdf*.

Blinders, Alan S. (1973) "Wage discrimination: reduced form and structural estimates," *Journal of Human Resources*, Vol. 8, pp. 436–455.

Blume, Marshall E and Donald B Keim (2012) "Institutional investors and stock market liquidity: trends and relationships," *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Boller, Lysle and Fiona Scott Morton (2020) "Testing the theory of common stock ownership," *NBER Working Paper*.

Butters, Gerard R (1977) "Equilibrium Distributions of Sales and Advertising Prices," *The Review of Economic Studies*, Vol. 44, pp. 465–491.

Callaway, Brantly and Pedro H.C. Sant'Anna (2021) "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, Vol. 225, pp. 200–230.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline (2018) "Firms and labor market inequality: Evidence and some theory," *Journal of Labor Economics*, Vol. 36, pp. S13–S70.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer (2019) "The Effect of Minimum Wages on Low-Wage Jobs," *The Quarterly Journal of Economics*, Vol. 134, p. 1405–1454.

Coates, C, John (2018) "The future of corporate governance part I: the problem of twelve."

Curtis, E. Mark, Daniel G. Garrett, Eric Ohrn, Kevin A. Roberts, and Juan Carlos Suárez Serrato (2021) "Capital Investment and Labor Demand: Evidence from 21st Century Tax Policy," URL: https://jcsuarez.com/Files/Bonus_RDC.pdf.

Dube, Arindrajit, Jeff Jacobs, Suresh Naidu, and Siddharth Suri (2020) "Monopsony in online labor markets," *American Economic Review: Insights*, Vol. 2, pp. 33–46.

Elhauge, Einer (2015) "Horizontal shareholding," *Harv. L. Rev.*, Vol. 129, p. 1267.

Falato, Antonio, Hyunseob Kim, and Till von Wachter (2021) "Shareholder Power and the Decline of Labor," *Working Paper*.

Falch, Torberg (2010) "The Elasticity of Labor Supply at the Establishment Level," *Journal of Labor Economics*, Vol. 28, pp. 237–266, URL: http://www.jstor.org/stable/10.1086/649905, DOI: http://dx.doi.org/10.1086/649905.

Fichtner, Jan, Eelke M Heemskerk, and Javier Garcia-Bernardo (2017) "Hidden power of the Big Three? Passive index funds, re-concentration of corporate ownership, and new financial risk," *Business and Politics*, Vol. 19, pp. 298–326.

Forsythe, Eliza and Russell Weinstein (2021) "Recruiting Intensity, Hires, and Vacancies: Evidence from Firm-Level Data."

Goodman-Bacon, Andrew (2021) "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, Vol. 225, pp. 254–277.

Goolsbee, Austan and Chad Syverson (2019) "Monopsony power in higher education: A tale of two tracks,"Technical report, National Bureau of Economic Research.

Goshen, Zohar and Doron Levit (forthcoming) "Common Ownership and The Decline of the American Worker," *Duke Law Journal*.

Hamilton, Stephen F (2009) "Informative advertising in differentiated oligopoly markets," *International Journal of Industrial Organization*, Vol. 27, pp. 60–69.

Hotelling, Harold (1929) "Stability in Competition," *The Economic Journal*, Vol. 39, pp. 41–57.

Jarosch, Gregor, Jan Sebastian Nimczik, and Isaac Sorkin (2021) "Granular Search, Market Structure, and Wages," *Working Paper*.

Kitagawa, Evelyn M. (1955) "Components of a difference between two rates," *Journal of the American Statistical Association*, Vol. 50, pp. 1168–1194.

Knepper, Mattew (2020) "From the Fringe to the Fore: Labor Unions and Employee Compensation," *Review of Economics and Statistics*, Vol. 102, pp. 98–112.

Krueger, Alan B and Eric Posner (2018) "A proposal for protecting low-income workers from monopsony and collusion," *The Hamilton project policy proposal*, Vol. 5.

López, Ángel L and Xavier Vives (2019) "Overlapping ownership, R&D spillovers, and antitrust policy," *Journal of Political Economy*, Vol. 127, pp. 2394–2437.

Manning, Alan (2006) "A generalised model of monopsony," *The Economic Journal*, Vol. 116, pp. 84–100.

——— (2011) "Imperfect competition in the labor market," *Handbook of labor economics*, Vol. 4, pp. 973–1041.

——— (2021) "Monopsony in labor markets: a review," *ILR Review*, Vol. 74, pp. 3–26.

Marinescu, Ioana and Herbert Hovenkamp (2019) "Anticompetitive mergers in labor markets," *Ind. LJ*, Vol. 94, p. 1031.

Marx, Matt (forthcoming) "Employee Non-compete Agreements, Gender, and Entrepreneurship," *Organization Science*.

Matsudaira, Jordan D. (2013) "Monopsony in the Low-Wage Labor Market? Evidence from Minimum Nurse Staffing Regulations," *The Review of Economics and Statistics*, Vol. 96, pp. 92–102, URL: https://doi.org/10.1162/REST_a_00361, DOI: http://dx.doi.org/10.1162/REST_a_00361.

Naidu, Suresh and Eric A Posner (2021) "Labor Monopsony and the Limits of the Law," *Journal of Human Resources*, pp. 0219–10030R1.

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

Newham, Melissa, Jo Seldeslachts, and Albert Banal-Estanol (2018) "Common Ownership and Market Entry: Evidence from Pharmaceutical Industry."

Oaxaca, Ronald (1973) "Male-female wage differentials in urban labor market," *International Economic Review*, Vol. 14, pp. 693–709.

Posner, Eric A (2021) "Policy implications of the common ownership debate," *The Antitrust Bulletin*, Vol. 66, pp. 140–149.

Posner, Eric A, Fiona M Scott Morton, and E Glen Weyl (2017) "A proposal to limit the anti-competitive power of institutional investors," *Antitrust Law Journal, forthcoming*.

Prager, Elena and Matt Schmitt (2021) "Employer Consolidation and Wages: Evidence from Hospitals," *American Economic Review*, Vol. 111, pp. 397–427.

Qiu, Yue and Aaron Sojourner (2022) "Labor-market concentration and labor compensation," *Available at SSRN 3312197*.

Ransom, Michael R and David P. Sims (2010) "Estimating the Firm's Labor Supply Curve in a "New Monopsony" Framework: Schoolteachers in Missouri," *Journal of Labor Economics*, Vol. 28, pp. 331–355, URL: http://www.journals.uchicago.edu/doi/abs/10.1086/649904, DOI: http://dx.doi.org/10.1086/649904.

Rinz, Kevin (2020) "Labor market concentration, earnings, and inequality," *Journal of Human Resources*, pp. 0219–10025R1.

Robinson, Joan (1969) "The Economics of Imperfect Competititon," *Springer*.

Rock, Edward B and Daniel L Rubinfeld (2020) "Common Ownership and Coordinated Effects," *ANTITRUST LJ*, Vol. 83, p. 201.

Ruiz-Pérez, Alexandro (2019) "Market Structure and Common Ownership: Evidence from the US Airline Industry,"Technical report, CEMFI Working Paper.

Staiger, Douglas O, Joanne Spetz, and Ciaran S Phibbs (2010) "Is there monopsony in the labor market? Evidence from a natural experiment," *Journal of Labor Economics*, Vol. 28, pp. 211–236.

Steinbaum, Marshall (2021) "Common ownership and the corporate governance channel for employer power in labor markets," *The Antitrust Bulletin*, Vol. 66, pp. 123–139.

MAIN FIGURES AND TABLES

Figure I
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.

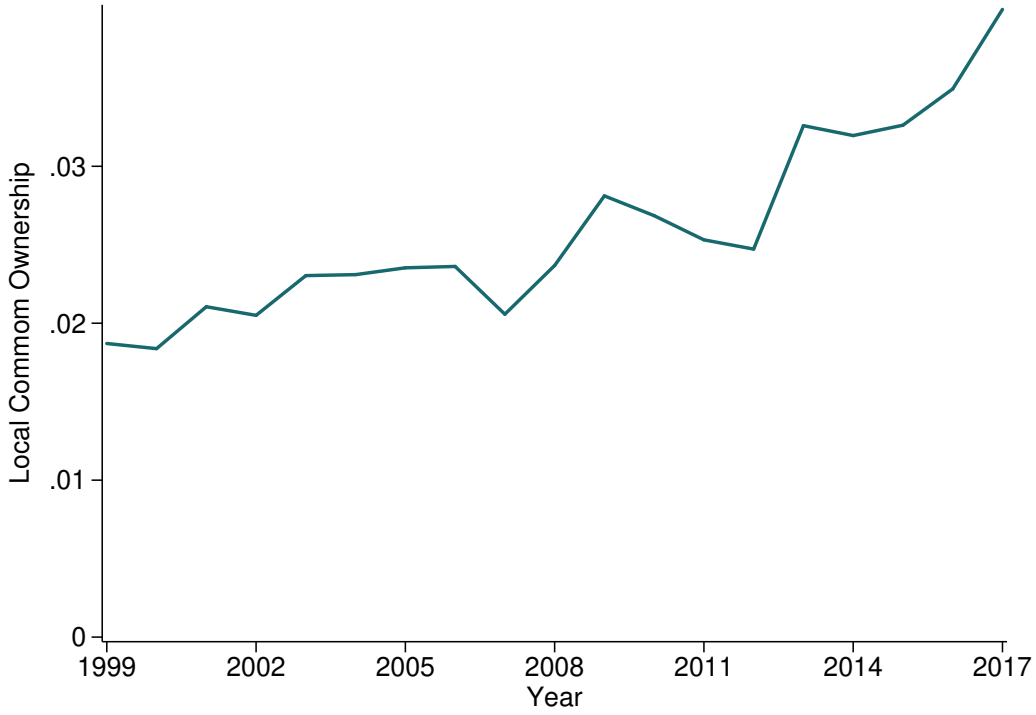


Figure II
Common Ownership Across Commuting Zones in 2017

This figure reports the average common ownership across commuting zones in 2017. In each commuting zone, we calculate the employment-weighed average common ownership across four-digit NAICS industries.

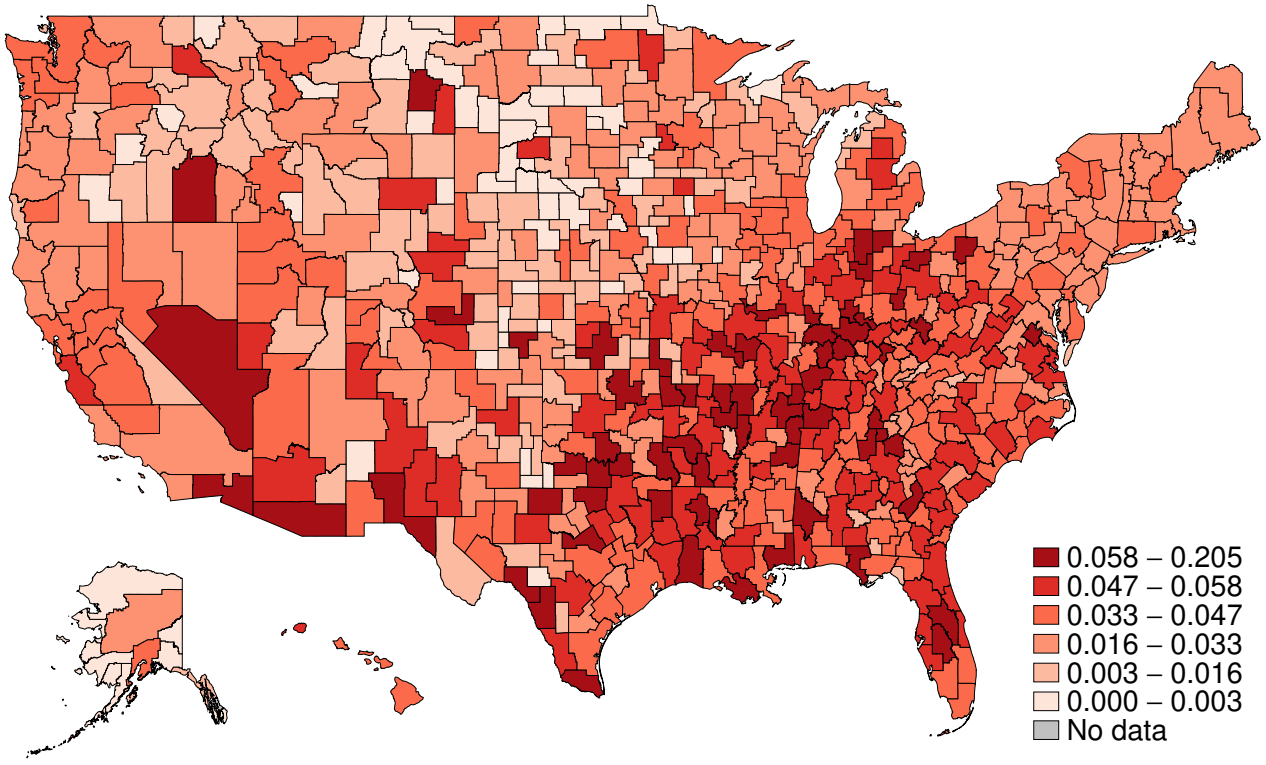


Figure III
Common Ownership Across Four-Digit NAICS Industries in 2017

This figure reports the top twenty four-digit NAICS industries in terms of average common ownership in 2017. In each four-digit NAICS industry, we calculate the employment-weighed average common ownership across commuting zones.

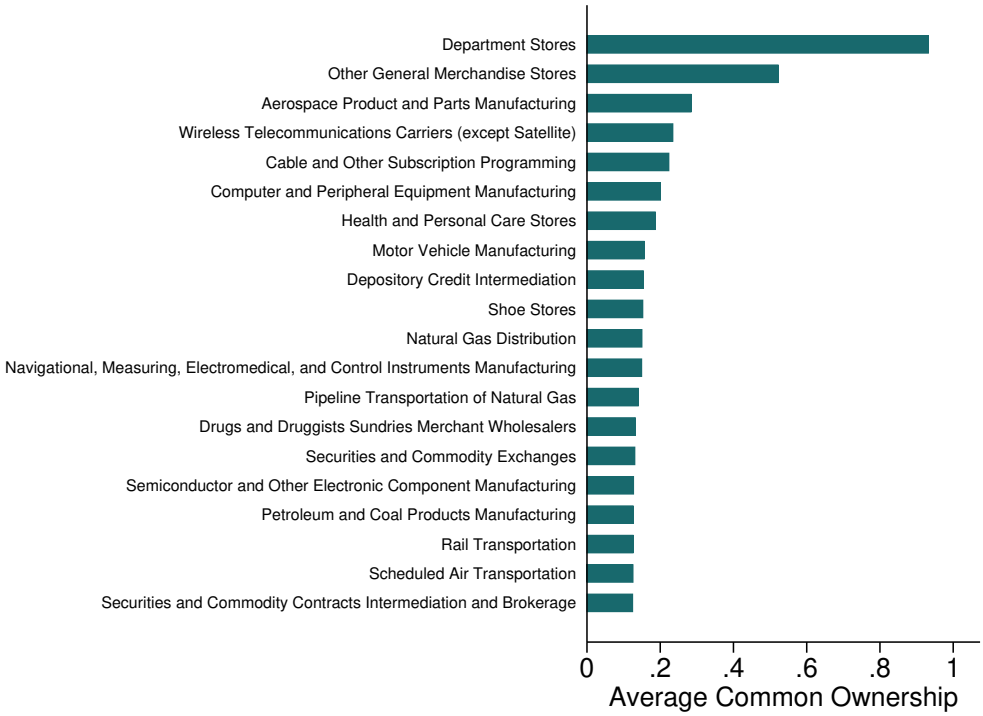


Figure IV
Effect of S&P 500 Index Additions on Common Ownership

This figure reports the estimates of equation (III. .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.

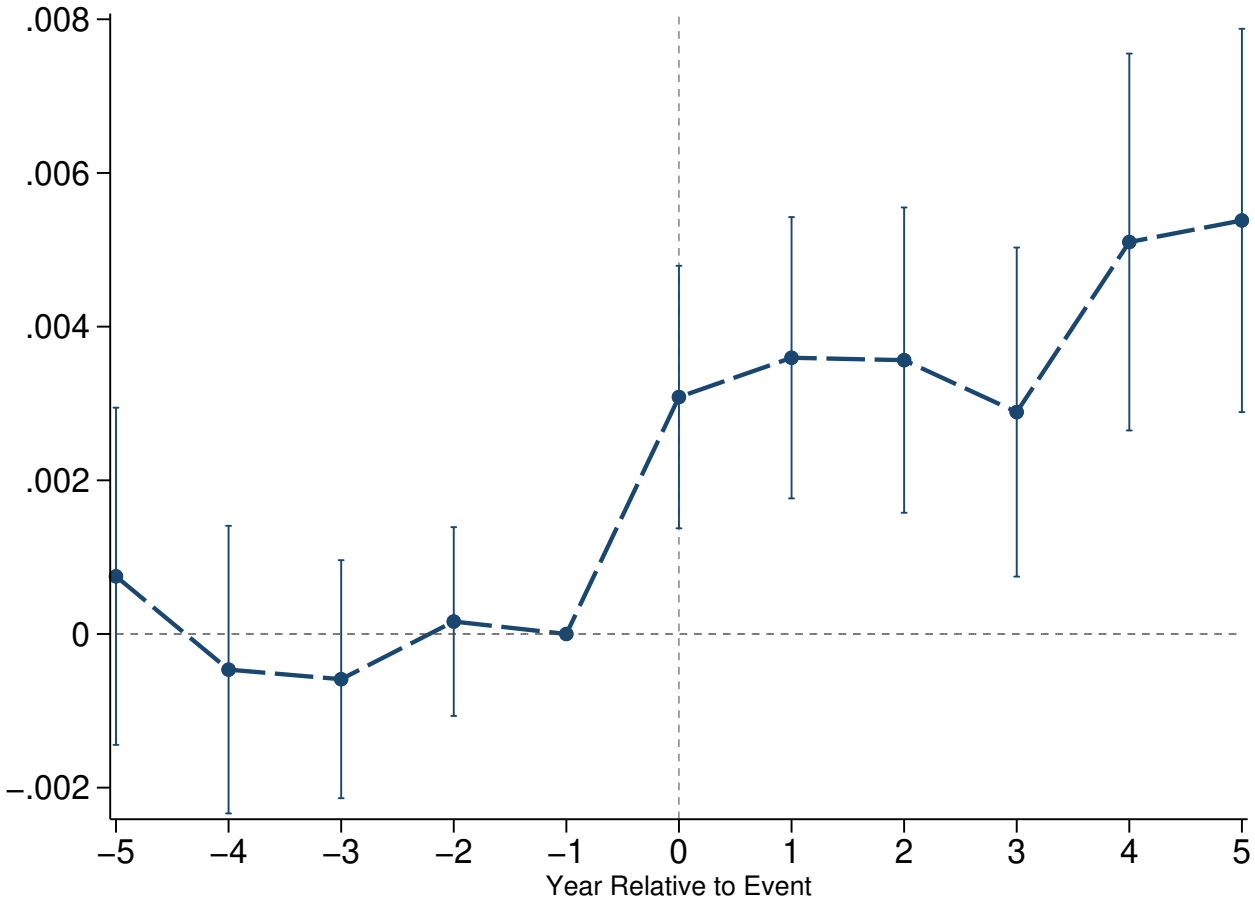


Figure V
Effect of S&P 500 Index Additions on Employee Earnings

This figure reports the estimates of equation (III. .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.

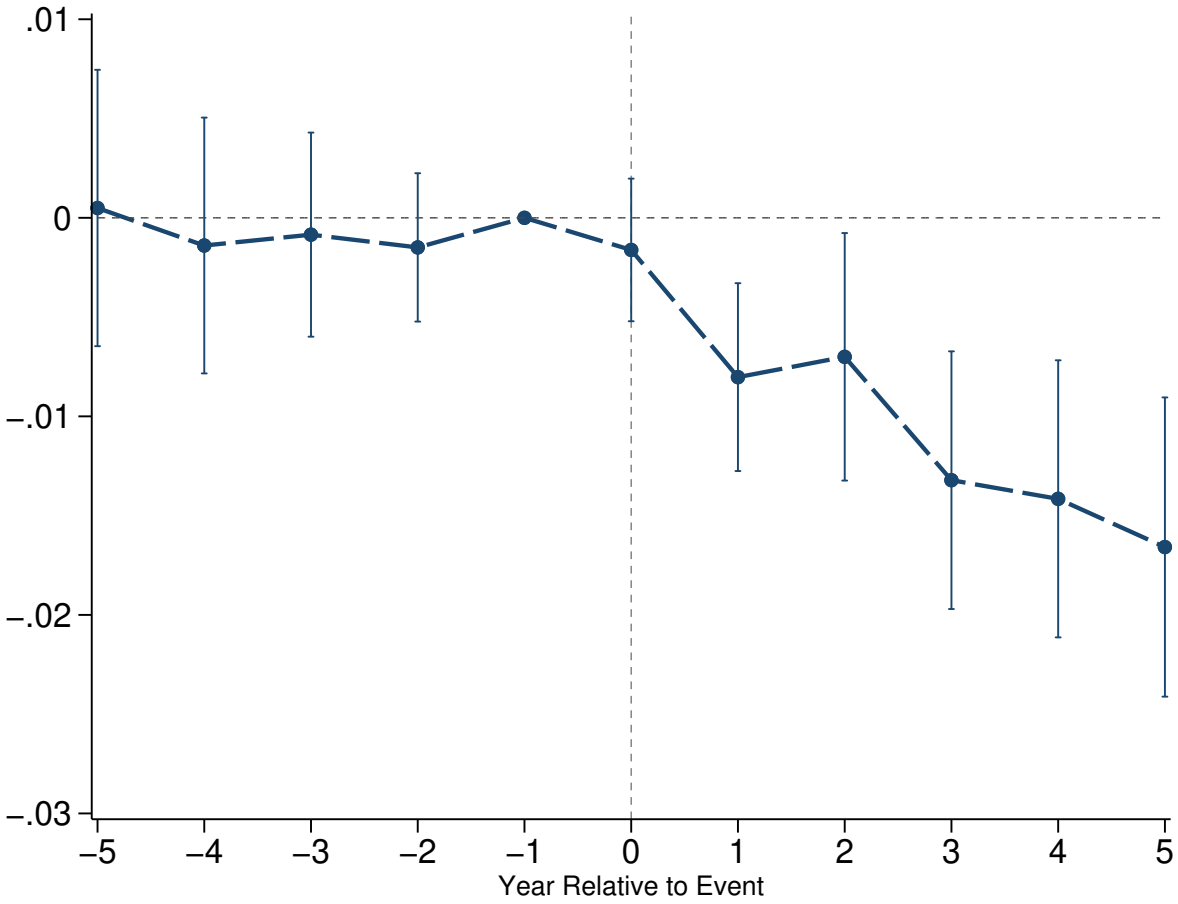


Figure VI
Heterogeneous Effects on Employee Earnings by Employment Share of S&P 500 Incumbents

This figure reports the estimates of equation (III. .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 they are based on standard errors clustered at the local labor market level.

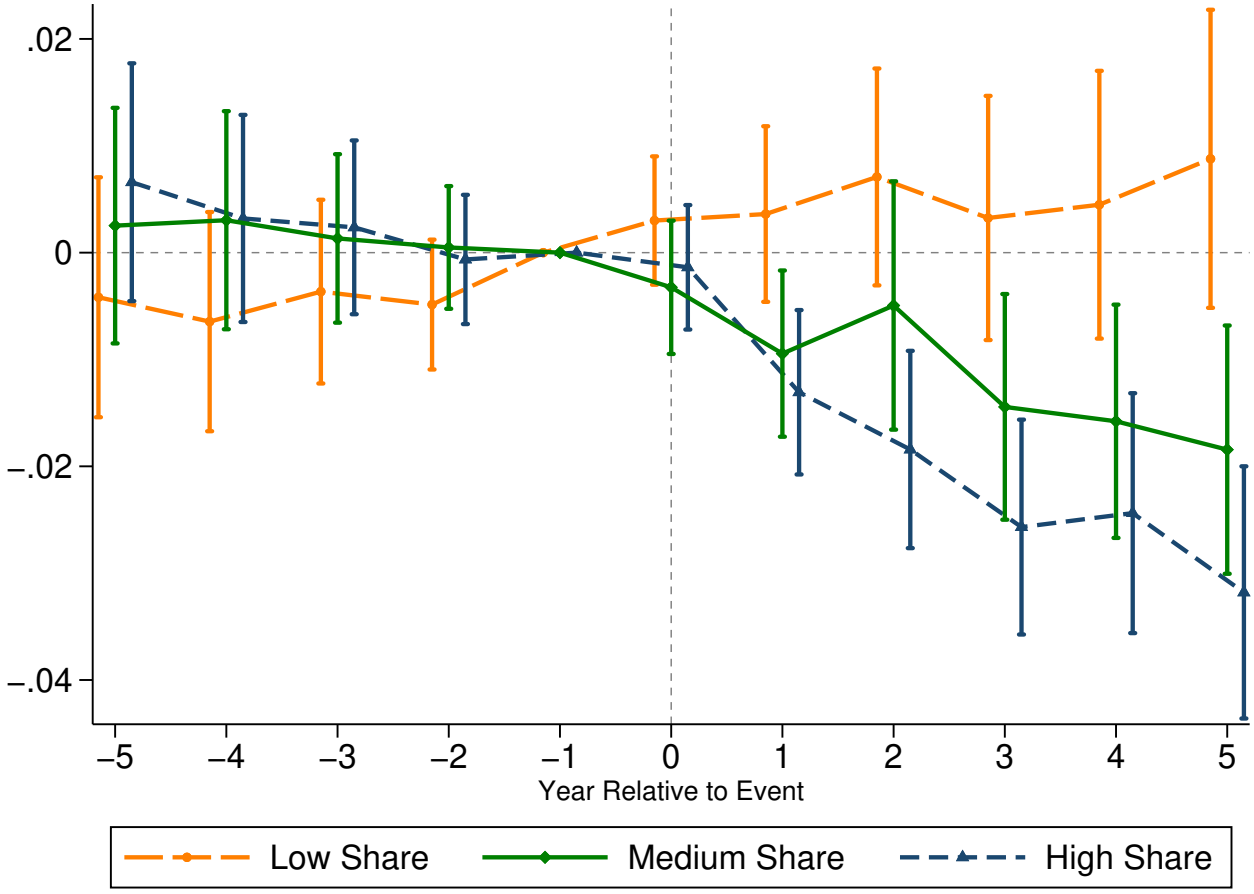


Figure VII
Heterogeneous Effects on Employee Earnings by Labor Union Power

This figure reports the estimates of equation (III. .1) for annual earnings per employee at the local labor market level conditional on pre-treament 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.

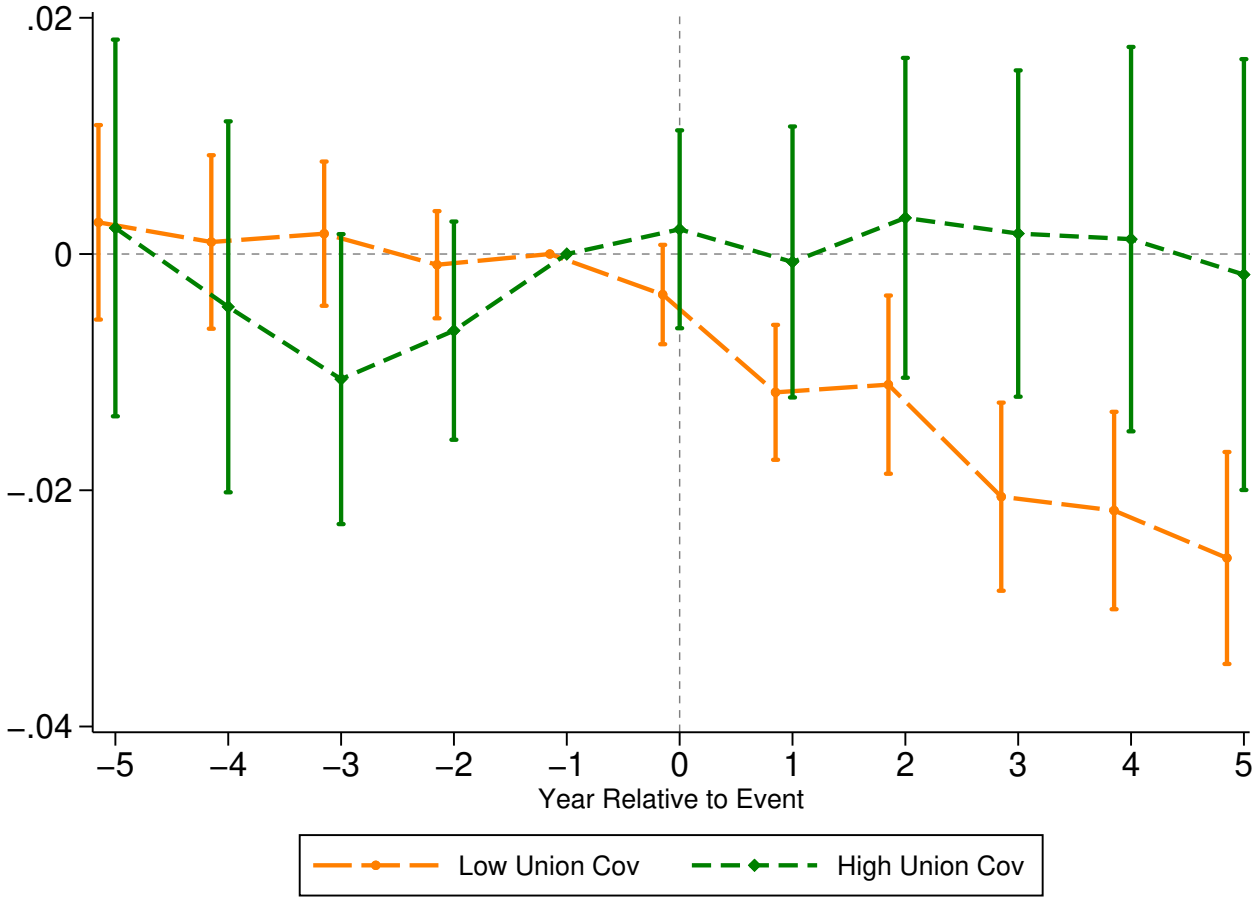


Figure VIII
Difference-in-Differences Analysis: Total Employment

This figure reports the estimates of equation (III. .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.

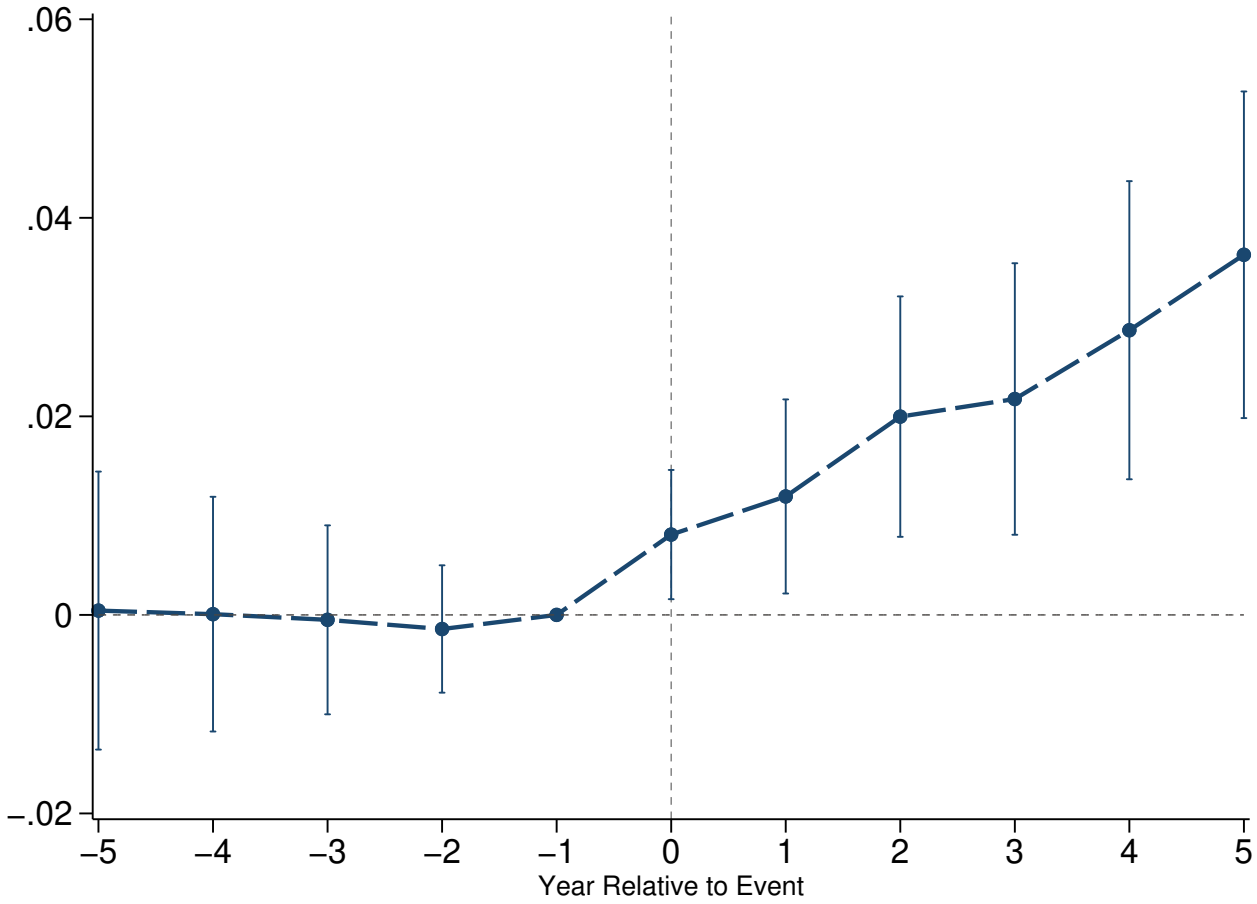


Figure IX
Difference-in-Differences Analysis: Hiring and Separation Rates

This figure reports the estimates of equation (III. .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.

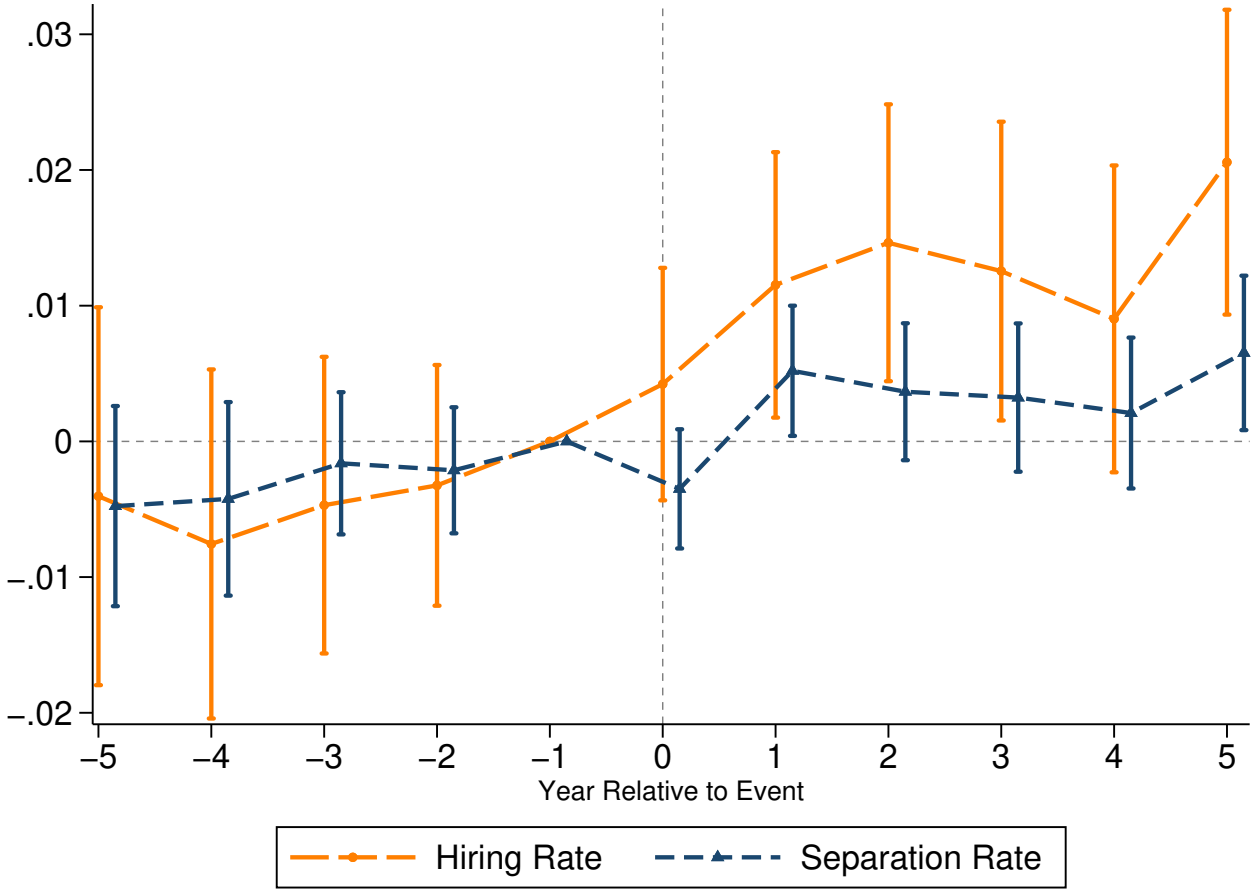
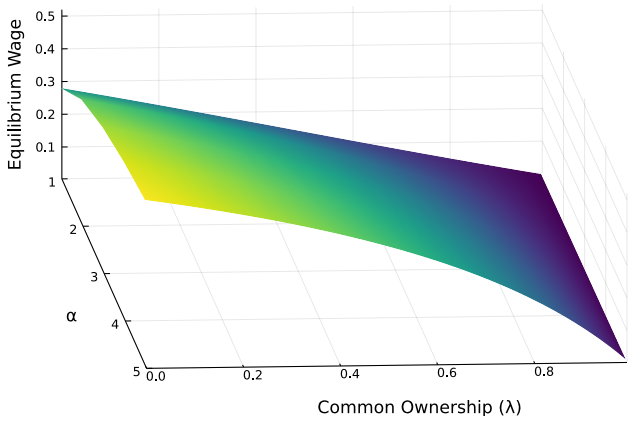
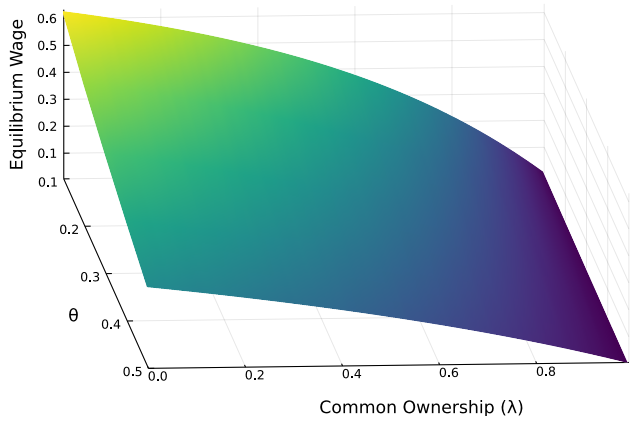


Figure X
Theoretical Effect of Common Ownership on Wages, Recruitment Intensity, and Employment

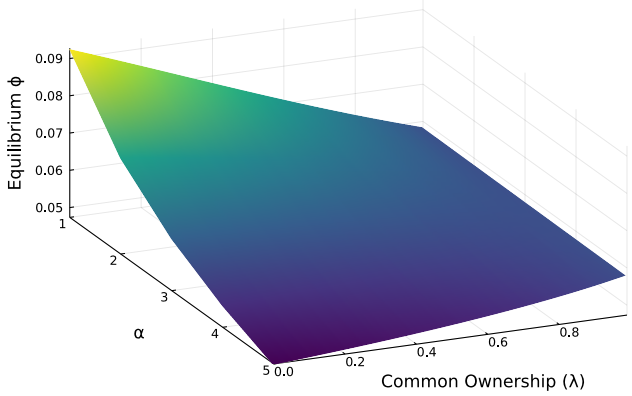
This figure shows the solution to the model for the following parameter values: number of firms $J = 20$, marginal product of labor $A = 1$ (as a normalization), cost of recruitment intensity parameter $\theta = 0.3$ (in the varying α case), and wage sensitivity parameter $\alpha = 3$ (in the varying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



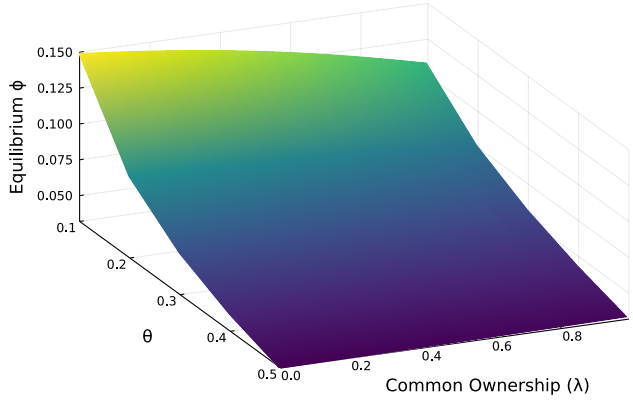
(a) Equilibrium Wage (Varying α)



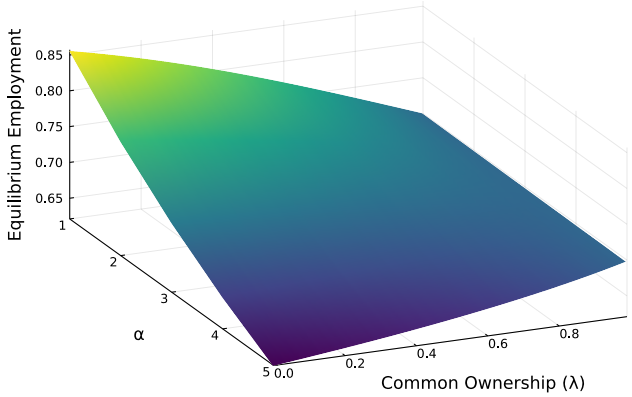
(b) Equilibrium Wage (Varying θ)



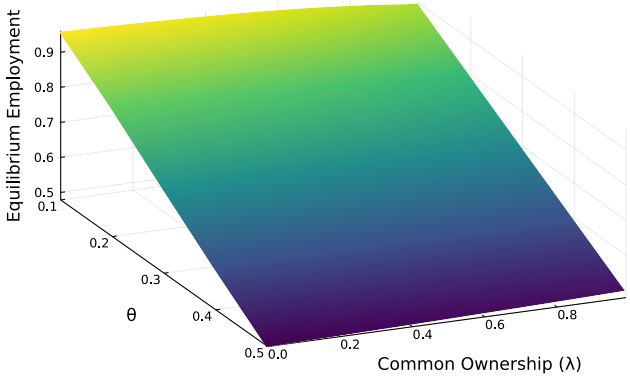
(c) Equilibrium Recruitment Intensity ϕ (Varying α)



(d) Equilibrium Recruitment Intensity ϕ (Varying θ)



(e) Equilibrium Employment (Varying α)



(f) Equilibrium Employment (Varying θ)

Table I
Summary Statistics of Outcome Variables and Covariates in DiD Analyses

This table reports the (unweighted) summary statistics of pre-treatment average of outcome variables and covariates in the DiD analysis. Annual Earnings per employee is in 2019 dollars. Variable definitions are available in Table A.1. Standard errors are double clustered at the four-digit NAICS and CZ level. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	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(Establishment Employment)	2,090	0.855	0.871	-0.016
25th Percentile of Log(Establishment Employment)	2,090	1.240	1.262	-0.022
50th Percentile of Log(Establishment Employment)	2,090	1.717	1.750	-0.034
75th Percentile of Log(Establishment Employment)	2,090	2.408	2.450	-0.042
90th Percentile of Log(Establishment Employment)	2,090	3.240	3.289	-0.049
Share of Public Firms' Employment	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 $\geq$ 20 & $\leq$ 44	2,090	0.344	0.344	-0.000
% Age $\geq$ 45 & $\leq$ 64	2,090	0.250	0.249	0.000
% Age $\geq$ 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

Table II
Effects on Workforce Characteristics

Panel A of this table reports the estimates of equation (III. .2) for workforce characteristics at the local labor market level. Panel B reports the estimates of equation (III. .2) after controlling for workforce characteristics at the local labor market level. Standard errors are clustered at the local labor market level. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Panel A: Effects on Workforce Composition

	% Less Educated	% Young	% Female	% Non-White	% Hispanic
	(1)	(2)	(3)	(4)	(5)
Treated×Post	-0.005***	0.006***	0.003***	0.003***	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[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×Post	-0.011***	-0.013***	-0.010***	-0.009***	-0.009***	-0.009***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
% Less Educated		-0.444***	-0.425***	-0.456***	-0.451***	-0.434***
		[0.047]	[0.046]	[0.045]	[0.047]	[0.046]
% Young Workers			-0.410***	-0.381***	-0.377***	-0.373***
			[0.027]	[0.026]	[0.026]	[0.026]
% Female				-0.549***	-0.548***	-0.561***
				[0.036]	[0.036]	[0.036]
% Non-White					-0.043	-0.043
					[0.058]	[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 III
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 pre-treatment 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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

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

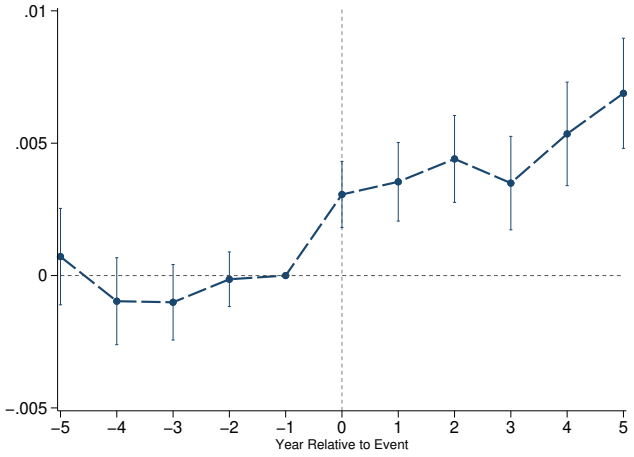
	Δ% Less Educated	Δ% Young	Δ% Female	Δ% Non-White	Δ% Hispanic
Treated Local Labor Markets	-0.004	-0.021	-0.003	0.011	0.011
Control Local Labor Markets	0.001	-0.028	-0.006	0.008	0.011
Contribution	0.256	-0.354	-0.093	-0.106	0.182

APPENDIX FIGURES AND TABLES

Figure A.1
Robustness: Include CZ Fixed Effects

This figure reports the estimates of equation (III. .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.

(a) Common Ownership



(b) Log(Annual Earnings per Employee)

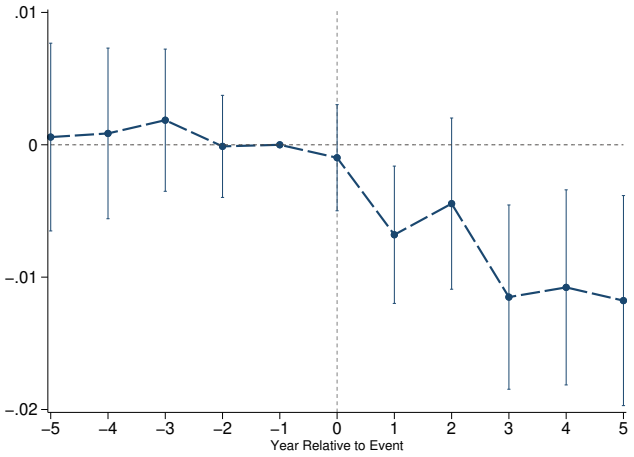
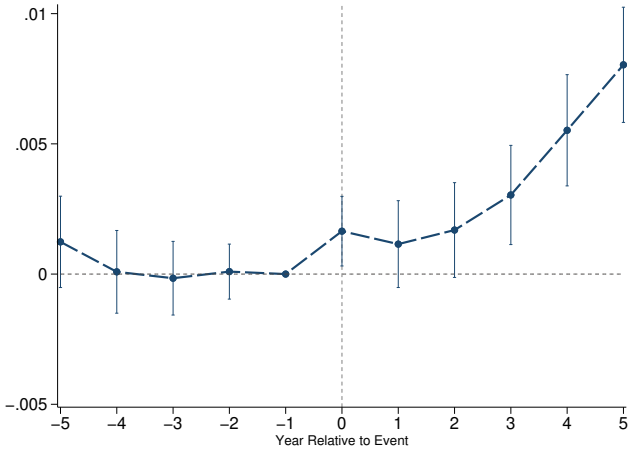


Figure A.2
Robustness: Thomson Reuters 13F Data

This figure reports the estimates of equation (III. .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)

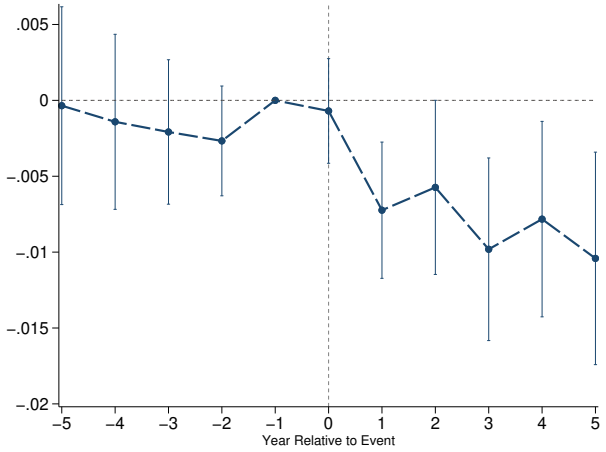
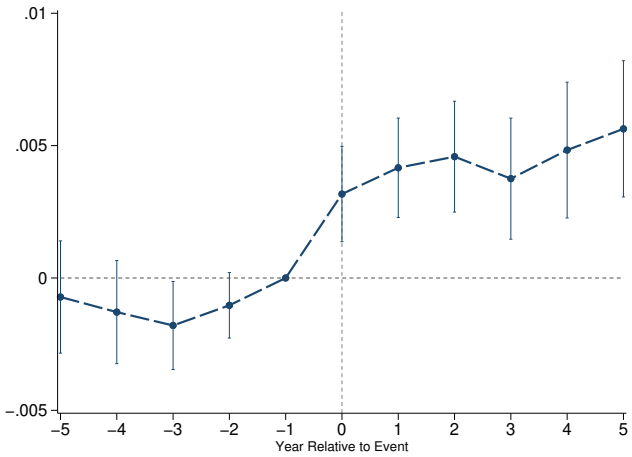


Figure A.3
Robustness: Alternative Definition of a Local Labor Market

This figure reports the estimates of equation (III. .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)

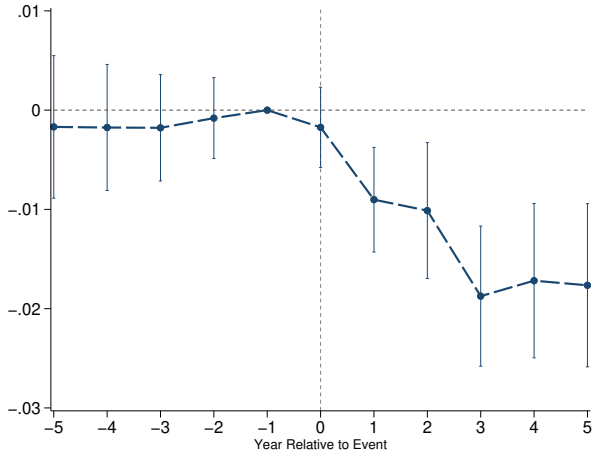


Table A.1
Variable Definitions

Variable	Definition
Panel Regression Analyses	
Log(Annual Earnings per Employee)	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 × four-digit NAICS level from QCEW. *Source:* QCEW.
Common Ownership	Average common ownership in a local labor market. It is calculated according to equation (2.1). *Source:* Data Axle and institutional ownership data from Backus et al. (2021b).
Total Institutional Ownership	Average total institutional ownership in a local labor market. It is calculated according to the equation in footnote 5. *Source:* Data Axle and institutional ownership data from Backus et al. (2021b).
Top5 Institutional Ownership	Average top5 institutional ownership in a local labor market. It is calculated according to the equation in footnote 5. *Source:* Data Axle and institutional ownership data from Backus et al. (2021b).
Difference-in-Differences Analyses	
Outcome Variables	
Log(Annual Earnings per Employee)	The natural logarithm of annual earnings per employee excluding county×five-digit NAICS cells containing firms entering to the S&P 500 index in a local labor market. *Source:* QCEW.
Common Ownership	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). *Source:* Data Axle and institutional ownership data from Backus et al. (2021b).
Log(Employment)	The natural logarithm of total employment excluding county×five-digit NAICS cells containing firms entering to the S&P 500 index in a local labor market. *Source:* QCEW.
local labor market Characteristics	
10th percentile of Log(Estab Emp)	The pre-treatment mean of the 10th percentile of the natural logarithm of establishment employment in a local labor market. *Source:* Data Axle.
25th percentile of Log(Estab Emp)	The pre-treatment mean of the 25th percentile of the natural logarithm of establishment employment in a local labor market. *Source:* Data Axle.
Median percentile of Log(Estab Emp)	The pre-treatment mean of the median of the natural logarithm of establishment employment in a local labor market. *Source:* Data Axle.
75th percentile of Log(Estab Emp)	The pre-treatment mean of the 75 percentile of the natural logarithm of establishment employment in a local labor market. *Source:* Data Axle.

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

Table A.2
Difference-in-Differences Analysis: Effect of S&P 500 Index Additions on Common Ownership and Annual Earnings per Employee

This table reports the estimates of equations (III. .1) and (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated×Post	0.004***		-0.011***	
	[0.001]		[0.003]	
Treated×Year(-5)		0.001		0.000
		[0.001]		[0.004]
Treated×Year(-4)		-0.000		-0.001
		[0.001]		[0.003]
Treated×Year(-3)		-0.001		-0.001
		[0.001]		[0.003]
Treated×Year(-2)		0.000		-0.001
		[0.001]		[0.002]
Treated×Year(0)		0.003***		-0.002
		[0.001]		[0.002]
Treated×Year(+1)		0.004***		-0.008***
		[0.001]		[0.002]
Treated×Year(+2)		0.004***		-0.007**
		[0.001]		[0.003]
Treated×Year(+3)		0.003***		-0.013***
		[0.001]		[0.003]
Treated×Year(+4)		0.005***		-0.014***
		[0.001]		[0.004]
Treated×Year(+5)		0.005***		-0.017***
		[0.001]		[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 (III. .1) and (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Panel A: Average Treatment Effect

	Low Share	Medium Share	High Share
	(1)	(2)	(3)
Treated×Post	0.008	-0.013***	-0.024***
	[0.005]	[0.005]	[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×Year(-5)	-0.004	0.003	0.007
	[0.006]	[0.006]	[0.006]
Treated×Year(-4)	-0.006	0.003	0.003
	[0.005]	[0.005]	[0.005]
Treated×Year(-3)	-0.004	0.001	0.002
	[0.004]	[0.004]	[0.004]
Treated×Year(-2)	-0.005	0.000	-0.001
	[0.003]	[0.003]	[0.003]
Treated×Year(0)	0.003	-0.003	-0.001
	[0.003]	[0.003]	[0.003]
Treated×Year(+1)	0.004	-0.009**	-0.013***
	[0.004]	[0.004]	[0.004]
Treated×Year(+2)	0.007	-0.005	-0.018***
	[0.005]	[0.006]	[0.005]
Treated×Year(+3)	0.003	-0.014***	-0.026***
	[0.006]	[0.005]	[0.005]
Treated×Year(+4)	0.004	-0.016***	-0.024***
	[0.006]	[0.006]	[0.006]
Treated×Year(+5)	0.009	-0.018***	-0.032***
	[0.007]	[0.006]	[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 (III. .1) and (III. .2) for annual earnings per employee at the local labor market level by pre-treatment mean of union coverage rates. Columns (1)—(2) report results for local labor markets with low pre-treatment mean of union coverage rates. Columns (3)—(4) report results for local labor markets with high pre-treatment mean of union coverage rates. Standard errors are clustered at the local labor market level. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	Low Union Cov	Low Union Cov	High Union Cov	High Union Cov
	(1)	(2)	(3)	(4)
Treated × Post	-0.018***		0.004	
	[0.004]		[0.007]	
Treated × Year(-5)		0.003		0.002
		[0.004]		[0.008]
Treated × Year(-4)		0.001		-0.004
		[0.004]		[0.008]
Treated × Year(-3)		0.002		-0.011*
		[0.003]		[0.006]
Treated × Year(-2)		-0.001		-0.006
		[0.002]		[0.005]
Treated × Year(0)		-0.003		0.002
		[0.002]		[0.004]
Treated × Year(+1)		-0.012***		-0.001
		[0.003]		[0.006]
Treated × Year(+2)		-0.011***		0.003
		[0.004]		[0.007]
Treated × Year(+3)		-0.021***		0.002
		[0.004]		[0.007]
Treated × Year(+4)		-0.022***		0.001
		[0.004]		[0.008]
Treated × Year(+5)		-0.026***		-0.002
		[0.005]		[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 (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	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***	0.003***	0.003***	0.002***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[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***	-0.009***	-0.008***	-0.008***	-0.008***
	[0.003]	[0.003]	[0.003]	[0.003]	[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 (III. .1) and (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated×Post	0.004***		-0.009***	
	[0.001]		[0.003]	
Treated×Year(-5)		0.001		0.001
		[0.001]		[0.004]
Treated×Year(-4)		-0.001		0.001
		[0.001]		[0.003]
Treated×Year(-3)		-0.001		0.002
		[0.001]		[0.003]
Treated×Year(-2)		-0.000		-0.000
		[0.001]		[0.002]
Treated×Year(0)		0.003***		-0.001
		[0.001]		[0.002]
Treated×Year(+1)		0.004***		-0.007**
		[0.001]		[0.003]
Treated×Year(+2)		0.004***		-0.004
		[0.001]		[0.003]
Treated×Year(+3)		0.003***		-0.012***
		[0.001]		[0.004]
Treated×Year(+4)		0.005***		-0.011***
		[0.001]		[0.004]
Treated×Year(+5)		0.007***		-0.012***
		[0.001]		[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 (III. .1) and (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated×Post	0.003***		-0.007**	
	[0.001]		[0.003]	
Treated×Year(-5)		0.001		-0.000
		[0.001]		[0.003]
Treated×Year(-4)		0.000		-0.001
		[0.001]		[0.003]
Treated×Year(-3)		-0.000		-0.002
		[0.001]		[0.002]
Treated×Year(-2)		0.000		-0.003
		[0.001]		[0.002]
Treated×Year(0)		0.002**		-0.001
		[0.001]		[0.002]
Treated×Year(+1)		0.001		-0.007***
		[0.001]		[0.002]
Treated×Year(+2)		0.002*		-0.006*
		[0.001]		[0.003]
Treated×Year(+3)		0.003***		-0.010***
		[0.001]		[0.003]
Treated×Year(+4)		0.006***		-0.008**
		[0.001]		[0.003]
Treated×Year(+5)		0.008***		-0.010***
		[0.001]		[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 (III. .1) and (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	Common Ownership	Common Ownership	Annual Earnings per per Employee	Annual Earnings per Employee
	(1)	(2)	(3)	(4)
Treated×Post	0.005***		-0.013***	
	[0.001]		[0.003]	
Treated×Year(-5)		-0.001		-0.002
		[0.001]		[0.004]
Treated×Year(-4)		-0.001		-0.002
		[0.001]		[0.003]
Treated×Year(-3)		-0.002**		-0.002
		[0.001]		[0.003]
Treated×Year(-2)		-0.001		-0.001
		[0.001]		[0.002]
Treated×Year(0)		0.003***		-0.002
		[0.001]		[0.002]
Treated×Year(+1)		0.004***		-0.009***
		[0.001]		[0.003]
Treated×Year(+2)		0.005***		-0.010***
		[0.001]		[0.003]
Treated×Year(+3)		0.004***		-0.019***
		[0.001]		[0.004]
Treated×Year(+4)		0.005***		-0.017***
		[0.001]		[0.004]
Treated×Year(+5)		0.006***		-0.018***
		[0.001]		[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: Effect of S&P 500 Index Additions on Total Employment

This table reports the estimates of equations (III. .1) and (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	Log(Total Emp)	Log(Total Emp)
	(1)	(2)
Treated × Post	0.023***	
	[0.007]	
Treated × Year(-5)		0.000
		[0.007]
Treated × Year(-4)		0.000
		[0.006]
Treated × Year(-3)		-0.000
		[0.005]
Treated × Year(-2)		-0.001
		[0.003]
Treated × Year(0)		0.008**
		[0.003]
Treated × Year(+1)		0.012**
		[0.005]
Treated × Year(+2)		0.020***
		[0.006]
Treated × Year(+3)		0.022***
		[0.007]
Treated × Year(+4)		0.029***
		[0.008]
Treated × 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: Effect of S&P 500 Index Additions on Hiring and Separation Rates

This table reports the estimates of equations (III. .1) and (III. .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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	Hiring Rate	Hiring Rate	Separation Rate	Separation Rate
	(1)	(2)	(3)	(4)
Treated×Post	0.016***		0.007***	
	[0.004]		[0.002]	
Treated×Year(-5)		-0.004		-0.005
		[0.007]		[0.004]
Treated×Year(-4)		-0.008		-0.004
		[0.007]		[0.004]
Treated×Year(-3)		-0.005		-0.002
		[0.006]		[0.003]
Treated×Year(-2)		-0.003		-0.002
		[0.005]		[0.002]
Treated×Year(0)		0.004		-0.003
		[0.004]		[0.002]
Treated×Year(+1)		0.012**		0.005**
		[0.005]		[0.002]
Treated×Year(+2)		0.015***		0.004
		[0.005]		[0.003]
Treated×Year(+3)		0.013**		0.003
		[0.006]		[0.003]
Treated×Year(+4)		0.009		0.002
		[0.006]		[0.003]
Treated×Year(+5)		0.021***		0.007**
		[0.006]		[0.003]
Pair-Local Labor Market FEs	✓	✓	✓	✓
Pair-Year FEs	✓	✓	✓	✓
Adjusted R^2	0.840	0.840	0.869	0.869
N	226,116	226,116	226,116	226,116

Table A.11
Summary Statistics of Panel Regression Sample

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	42805.253	25686.284	18304.795	38220.980	70897.578
Employment	1,392,835	1275.759	5505.857	21.000	198.000	2474.000
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

Table A.12
Panel Regressions: 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. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Common Ownership	-0.040***	-0.050***	-0.047***	-0.109***	-0.192***	-0.181***
	[0.006]	[0.006]	[0.006]	[0.016]	[0.017]	[0.016]
Total Institutional Ownership		0.011	0.016**		0.120***	0.145***
		[0.008]	[0.008]		[0.023]	[0.023]
Top5 Institutional Ownership		0.009	-0.014		-0.059	-0.165**
		[0.019]	[0.018]		[0.065]	[0.065]
local labor market FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓		✓	✓	
CZ×Year FEs			✓			✓
Kleibergen-Paap rk Wald F-stat				5611.21	1791.34	1783.45
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