Common Ownership Reduces Wages and Employment*

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Abstract

In this study, we examine the effects of common ownership on labor market outcomes. We find that an increase in common ownership in a labor market is associated with decreases in both wages per employee and the employment-to-population ratio. We conduct an event study based on the acquisition of Barclays Global Investors by BlackRock in 2009. Using a synthetic control method, we find that markets that were more affected by the acquisition experienced post-acquisition decreases in annual wages per employee and employment-to-population ratio relative to the counterfactual of no acquisition. The estimated treatment effects of the acquisition were stronger in markets with higher unemployment rates, lower personal income per capita, lower population density, and stricter enforcement of noncompete clauses.

Keywords: Monopsony, Oligopsony, Labor Markets, Competition Policy, Common Ownership

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1 Introduction

One of the most salient trends in the U.S. economy during the second half of the twentieth century and the beginning of the twenty-first is the rise of institutional ownership. Ownership of U.S. equities by institutions went from less than 10% in 1953 to more than 60% in 2005 (Gillan and Starks, 2015). Together with the shift in assets from actively managed funds to passively managed index funds, this has led to a large increase in common ownership for publicly traded firms in the United States in the past four decades (see, for example, Azar and Vives, 2021*a*; Backus, Conlon and Sinkinson, 2021*b*).[1] This trend has raised the alarm that a small number of giant asset managers could effectively control most large publicly traded firms in the near future (Coates, 2018). One reason for this concern is that the common ownership trend, at least theoretically, could contribute to the wage stagnation observed in the U.S. economy since the 1970s (Goshen and Levit, 2021; Steinbaum, 2021; Azar and Vives, 2021*a*).[2] However, little is known about the common ownership effects on labor market outcomes empirically. In this paper, we fill this gap and provide the first empirical evidence on the effects of common ownership on labor market outcomes such as wages and employment.

To motivate the empirical analysis, we develop a model of an oligopsonistic labor market with common ownership. In the model, workers' labor supply decisions are based on a nested logit utility model, and firms are assumed to be connected via common shareholders. If shareholders of a firm partially internalize the profits of rival firms, then our model predicts that, in equilibrium, a higher level of common ownership among firms in a market leads to a higher wedge between the marginal product of labor and employee wages, resulting in lower equilibrium wages per employee and employment-to-population ratio. We then calibrate the model based on the estimates from Azar, Berry and Marinescu (2019), and show that in the calibrated model the sensitivity of labor market outcomes to common ownership is lower when workers have better outside options.

We then test the theoretical predictions empirically. We define a labor market as the interaction between a 4-digit NAICS industry and a core-based statistical area (CBSA) (a local industry hereafter). Data on annual wages per employee and total employment in a local industry is from the annual average files from the Quarterly Census of Employment and Wages (QCEW). Employment-to-population ratio at the local industry level is defined as the ratio of local industry-level total employment to the CBSA's 20-64 year old population. To measure

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

common ownership in a local industry, we combine firm-level ownership data from Backus, Conlon and Sinkinson (2021*b*) with local industry-level firm employment share constructed from Data Axle, a marketing company. In particular, for any two firms i and j in a local industry, we measure common ownership, λ_{ij}, as the weight that firm i puts on the profit of firm j following the approach of Azar (2012, ch. 7) and Backus, Conlon and Sinkinson (2021*a*). To aggregate common ownership to the local industry level, we follow Azar and Vives (2021*b*). Specifically, for each firm in a local industry, we first calculate the weighted average of the pair-wise common ownership measures by the employment shares of the local rival firms and then calculate the employment-weighted average of the constructed firm-level measures.

To estimate the common ownership effects on labor market outcomes, we use two approaches. The first approach is based on estimating a linear regression model of wages and employment rates as functions of common ownership and a set of control variables. We run both OLS and 2SLS panel regressions. Our instrumental variable (IV) for common ownership in a local industry is the average of the equally-weighted local common ownership for the same industry in other CBSAs in a given year.

The main identification assumption in our IV analysis is that ownership itself is exogenous, which is commonly assumed in the structural common ownership literature (see, for example, Backus, Conlon and Sinkinson, 2021*a*; Ruiz-Pérez, 2019). This IV purges our explanatory variable of any idiosyncratic variation in local common ownership or variation that is driven by changing labor market shares, and focuses on the part of variation that is driven by nationwide changes in common ownership. Both OLS and 2SLS results suggest that an increase in common ownership in a local industry is associated with decreases in both annual wages per employee and the employment-to-population ratio, but the magnitudes of 2SLS estimates are much larger. In the specification with local industry and CBSA$\times$year fixed effects, OLS estimates suggest that a one-standard-deviation increase in local common ownership is associated with a 0.34% decrease in annual wages per employee and a 0.46% decrease in the employment-to-population ratio relative to the sample mean, while 2SLS regression results show that the estimated effects of a one-standard-deviation increase in local common ownership on employee wages and employment-to-population ratio are -1.31% and -6.64% relative to sample mean, respectively.

Our second strategy is based on a natural experiment generated by the acquisition of Barclays Global Investors (BGI) by Blackrock (BLK) in 2009. We use the variation in common ownership across labor markets generated by this acquisition to estimate common ownership effects on labor market outcomes. This approach further mitigates the concerns in the IV analysis that local shocks driving both labor market outcomes and common ownership are correlated across CBSAs. Others have used this acquisition to study the common ownership effects on product markets, including Azar, Schmalz and Tecu (2018).

This acquisition changed the degree of local common ownership differently but predictably in each local industry, making it an appealing source of variation to leverage. To measure the extent to which a local industry is affected by the acquisition, we construct a measure of the predicted acquisition-induced change in local common ownership for each local industry using pre-acquisition ownership and employment information. Specifically, for each local industry in 2008, we first calculate the local industry common ownership using the realized ownership information in the last pre-acquisition quarter (2009 Q1) and then calculate the same measure assuming that BLK and BGI were already one entity. The difference between the implied common ownership level if the acquisition had already occurred and the observed local industry common ownership is the change in common ownership implied by the acquisition, $\Delta\lambda$, excluding endogenous post-acquisition changes in ownership shares.

To estimate the treatment effects of the BLK-BGI acquisition on local industry wages and employment to population ratio, we employ the synthetic control method developed in Robbins, Saunders and Kilmer (2017). Compared to the canonical synthetic control method in Abadie, Diamond and Hainmueller (2010), the major advantage of this newly developed method is that it is feasible to construct a synthetic control comparison that can simultaneously match across multiple time-varying outcomes (local industry-level common ownership, employee wages, and employment-to-population ratio) and time-invariant covariates (average distribution of employment and employment share of publicly traded firms at the local industry level during the pre-acquisition period). A local industry is defined to be treated if its $\Delta\lambda$ is above the sample median of strictly positive $\Delta\lambda$s, and to be a control local industry if its $\Delta\lambda$ is below the sample median of strictly positive $\Delta\lambda$s, or its $\Delta\lambda$ is equal to zero.

The synthetic control estimation results show that the BLK-BGI acquisition caused an increase in local common ownership, a decrease in annual wages per employee, and a decrease in employment-to-population ratio in treated local industries. Specifically, between 2010 and 2017, our estimations show that local common ownership increases 6.2 percentage points more in our treated markets than our control markets, and the estimated effect is statistically significant at the 5% level. During the same time, we also observe a 2.9% decrease in annual wages per employee and a 4.7% decrease in the employment-to-population ratio relative to the sample mean in the pre-acquisition period. Both estimated effects are statistically significant at the 5% level. The results are consistent with the estimations from OLS and 2SLS regressions and suggest that local industries experiencing a larger increase in local common ownership induced by the BLK-BGI acquisition experience worse labor market outcomes in the post-acquisition period.

We also find that the estimated treatment effects of the BLK-BGI acquisition are heterogeneous, with the effects being larger in markets where workers' outside options are worse. We proxy the value of employees' outside options by four measures at the CBSA-level: (1) unemployment rate, (2) personal income per capita, (3) population density, and (4) enforcement index of noncompete clauses, all of which are measured as the average values during the pre-acquisition period. We split the treated local industries into ones with high and low value of employees' outside options and estimate the treatment effects on each subsample. We find that the estimated treatment effects of the BLK-BGI acquisition on employee wages and employment-to-population ratio are more negative when treated local industries are in CBSAs with higher unemployment rates, lower personal income per capita, lower population densities, and stricter enforcement of noncompete clauses. The results suggest that the adverse effects of common ownership on labor market outcomes are stronger when the value of employees' outside options is lower.

Our paper is related two strands of literature. First, our paper fits in the literature on the real effects of common ownership and we make two contributions. Our first contribution is providing the first measure of common ownership at the local industry level. Our second contribution is providing empirical evidence on how common ownership affects employee wages and employment at the local industry level. Prior studies focus on the effects of common ownership on product markets (see, for example, Azar, Schmalz and Tecu, 2018; Newham, Seldeslachts and Banal-Estanol, 2018; Ruiz-Pérez, 2019; Backus, Conlon and Sinkinson, 2021*a*), executive compensation (Antón et al., 2020), and innovation (López and Vives, 2019; Anton et al., 2018) but little is known about its effects on labor markets. We start to fill this gap, and our results suggest that both employee wages and the employment-to-population ratio decrease in local industries that experience an increase in common ownership. To the best of our knowledge, this is the first empirical evidence on the common ownership effects on labor market. With the availability of the common ownership measure at the local industry level, future research can shed more light on how common ownership affects labor market outcomes beyond employee wages and employment.

Our paper is also related to the literature on imperfect competition in labor market. Prior studies measure labor market power by employer concentration, in particular, the Herfindahl-Hirschman Index (HHI) based on either job posting share (Azar, Marinescu and Steinbaum, 2020) or employment share (Benmelech, Bergman and Kim, 2020; Prager and Schmitt, 2021; Rinz, 2020; Arnold, 2021; Qiu and Sojourner, 2019). The conclusion from these studies is that HHI in a labor market is negatively associated with employee wages at the market or establishment level. But employer concentration is only one source of employer market power and is far from the only one. We contribute to this literature by showing that, holding the structure of a labor market as constant, connections among firms via common shareholders would reinforce the labor market power. In our model, an increase in common ownership among firms leads to a higher wedge between the marginal product of labor and employee wages, which implies that employers have higher labor market power, and the equilibrium wages per employee and employment-to-population ratio are lower as a result. Consistent with the model predictions, we empirically find that an increase in common ownership in a labor market is indeed associated with decreases in both employee wages and employment-to-population ratio.

The rest of the paper is organized as follows. Section 2 describes the economic model motivating our empirical analysis. Section 3 describes the labor market and ownership datasets that we used, and provides summary statistics. Section 4 describes our empirical strategy. Section 5 presents the results from our main econometric analysis. Section 6 shows evidence on the heterogeneity of the effects of common ownership on labor markets depending on employees' outside options. Section 7 concludes. Several appendices provide definitions, proofs, and supplementary material.

2 Theoretical Framework

In this section, we develop an oligopsony model of a labor market. As in Azar, Berry and Marinescu (2019), we assume that the workers' labor supply decisions are based on a nested logit utility model, with an outside option in a different nest. On the labor demand side, we allow the firms in the model to be linked through a network of common ownership.

Consider the labor market of a local industry g with J firms that are hiring workers and post wages. The market is an oligopsony, with competition in wages and a continuum of people of working age of mass N. We interpret N as the working-age population in a geographic area. Person i's utility from working at firm j is of the nested logit form,

$$u_{ij} = v_j + \alpha \log(w_j) + \nu(\rho) + \rho\epsilon_{ij} \tag{2.1}$$

where v_j and w_j are the quality and wage of firm j's jobs, respectively. ϵ_{ij} is a worker-job-specific match value error term. We assume that ϵ_{ij} is independent and identically distributed, with a Type I extreme value distribution. There is an outside option with utility v_0, which represents employment in other industries, unemployment, or leaving the labor force (we can thus think of v_j as the utility of job j relative to the outside option $v_j = \tilde{v}_j - v_0$). We will model the outside option (working in another industry or not working) as being in its own nest, and the jobs from the local industry's labor market to be in another nest. We will do comparative statics relative to v_0, so we do not always want to normalize v_0 to zero. The parameter ρ is a market-specific nesting parameter and measures the substitutability between the nest where the outside option is and the nest where the local industry's jobs are.

The parameter ρ can go from zero to one. Larger ρ values express that the jobs in the local industry are more substitutable with the outside option. In the limit case when $\rho = 0$, the local industry is completely segmented from the outside option, in the sense that a person that could choose a job from the local industry would never choose the outside option. Vice-versa, when $\rho = 1$, the outside option is in the same nest as the jobs in the local industry. The error term $\nu(\rho)$ has a distribution such that $\nu(\rho) + \rho\epsilon_{ij}$ has a generalized extreme value distribution.

The employment share of firm j in the working-age population, s_j, is then characterized as the product of the employment share of firm j in the local industry's labor market $s_{j|g}$, and the local industry's employment share in the working-age population s_g (which is equal to one minus the share of the local population choosing the outside option s_0):

$$s_j(\mathbf{w}) = \underbrace{\frac{\exp\left[(v_j + \alpha \log(w_j))/\rho\right]}{D_g}}_{s_{j|g}} \times \underbrace{\frac{D_g^\rho}{1 + D_g^\rho}}_{s_g = 1 - s_0} \tag{2.2}$$

where

$$\log(D_g) \equiv \log\left\{\sum_{k=1}^{J} \exp\left[(v_k + \alpha \log(w_k))/\rho\right]\right\} \tag{2.3}$$

is the inclusive value of employment in the local industry to potential workers. To be more precise, the inclusive value captures potential workers' expected value of picking their favorite job in the industry.

The group share s_g measures the probability of a person in the local population being employed in the local industry. It is equal to the local industry's employment to population ratio in the model, and it's equal to one minus the share of the outside option $s_0 = 1/(1 + D_g^\rho)$. The within-group share $s_{j|g}$ measures the probability that an employee works for firm j in a market conditional on being employed in the local industry.

The profits of firm j are

$$\pi_j(\mathbf{w}) = (A_j - w_j)s_j(\mathbf{w}) \tag{2.4}$$

where A_j is the additional revenue for firm j from hiring another worker, and s_j is the labor market share of firm j, which is a function of the vector of firm wages in the market $\mathbf{w}$.

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

$$\zeta_j(\mathbf{w}) = \left(A_j - w_j\right) s_j(\mathbf{w}) + \lambda \cdot \left[\sum_{k \neq j} \left(A_k - w_k\right) s_k(\mathbf{w})\right]. \tag{2.5}$$

The first-order condition for firm j is:

$$\left(A_j - w_j\right) \frac{\partial s_j(\mathbf{w})}{\partial w_j} + \lambda \cdot \left[\sum_{k \neq j} \left(A_k - w_k\right) \frac{\partial s_k(\mathbf{w})}{\partial w_j}\right] = s_j(\mathbf{w}) \tag{2.6}$$

and the market share slopes are:

$$\frac{\partial s_k}{\partial w_j} = \begin{cases} \frac{\alpha}{\rho} s_j \left[1 - (1-\rho) s_{j|g} - \rho s_j\right] \frac{1}{w_j} & \text{if } k = j \\ -\frac{\alpha}{\rho} s_j \left[(1-\rho) s_{k|g} + \rho s_k\right] \frac{1}{w_j} & \text{if } k \neq j \end{cases} \tag{2.7}$$

From here on we will focus on the symmetric case with $A_j = A$ and $v_j = v$ for all j. In the symmetric case, $s_{j|g} = 1/J$, which is the Herfindahl-Hirschman index, and the equilibrium elasticity of labor supply to the firm is

$$\eta_j \equiv \frac{\partial \log s_j}{\partial \log w_j} = \frac{\alpha}{\rho} \left[1 - (1-\rho) \frac{1}{J} - \rho \frac{1}{J}(1 - s_0)\right] = \frac{\alpha}{\rho} \left[1 - (1/J)(1 - \rho s_0)\right]. \tag{2.8}$$

To go from elasticity to markdown, consider first the case of no common ownership ($\lambda = 0$). In this case, the first-order condition of the firm implies that the markdown is equal to the inverse elasticity of labor supply to the firm:

$$\mu^* \equiv \frac{A - w^*}{w^*} = \frac{1}{\frac{\alpha}{\rho}\left[1 - (1/J)(1 - \rho s_0)\right]} \tag{2.9}$$

In the case of $\lambda > 0$, the markdown has a similar form, but with a modified Herfindahl-Hirschman index (MHHI) instead of $1/J$. We denote this modified HHI with the letter H, such that $H \equiv \frac{1}{J} + \lambda \left(1 - \frac{1}{J}\right)$ (as in Azar and Vives, 2021*a*). In this case, we obtain the following expression for the equilibrium markdown:

$$\mu^* = \frac{1}{\frac{\alpha}{\rho}\left[1 - H(1 - \rho s_0)\right]}. \tag{2.10}$$

Thus, with common ownership the markdown is not proportional to the inverse elasticity, but to the inverse of a new object that we call the "modified elasticity" $\frac{\alpha}{\rho}\left[1 - H(1 - \rho s_0)\right]$, which captures the fact that the firm internalizes to some extent the diversion of employment to other commonly-owned firms in the market when it reduces its wage. The modified elasticity is lower than the actual elasticity, and therefore the markdown is higher when common ownership is higher.

The equilibrium log wage is

$$\log(w^*) = \log(A) - \log\left[1 + \mu^*(\lambda)\right] \tag{2.11}$$

Taking the derivative with respect to the exogenous common ownership parameter λ leads us to our main proposition:

Proposition 1. *An increase in the common ownership parameter λ generates:*

1. *an increase in the equilibrium markdown μ^*,*
2. *a decline in the equilibrium wage w^*, and*
3. *a decline in the equilibrium employment-population ratio $(1 - s_0^*)$.*

Proof: In Appendix. □

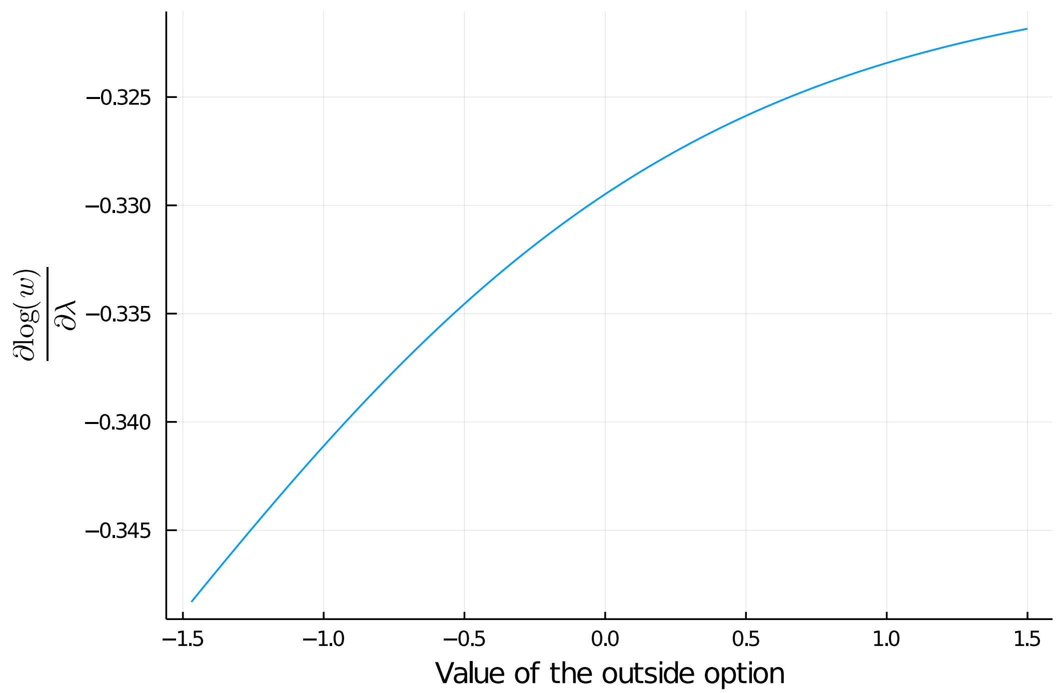
Thus, in a simple model of oligopsonistic wage competition with common ownership, an increase in common ownership among the firms in a labor market increases the equilibrium markdown of wages below the marginal product of labor, reduces equilibrium wages, and reduces the equilibrium employment-population ratio.

We have also explored heterogeneity in the derivatives of log wage and employment-population ratio with respect to λ as a function of the utility of the outside option. We calibrated the model using values for the parameters from Azar, Berry and Marinescu (2019). In particular, we $\alpha = 0.279$, $\rho = 0.148$, $J = 19$, we normalize $A = 1$, $v_0 = 0$ and choose $\tilde{v}$ chose to match the average share of the outside option in Azar, Berry and Marinescu (2019) (0.837). We set $\lambda = 0.04$ based on the average weight that firms in a local industrial labor market put on competing firms in 2017 in our data (see Figure 2 in Section 3). Note that, for the calibration, we normalize $v_0 = 0$, but then do comparative statics by considering changes in v_0 around zero.

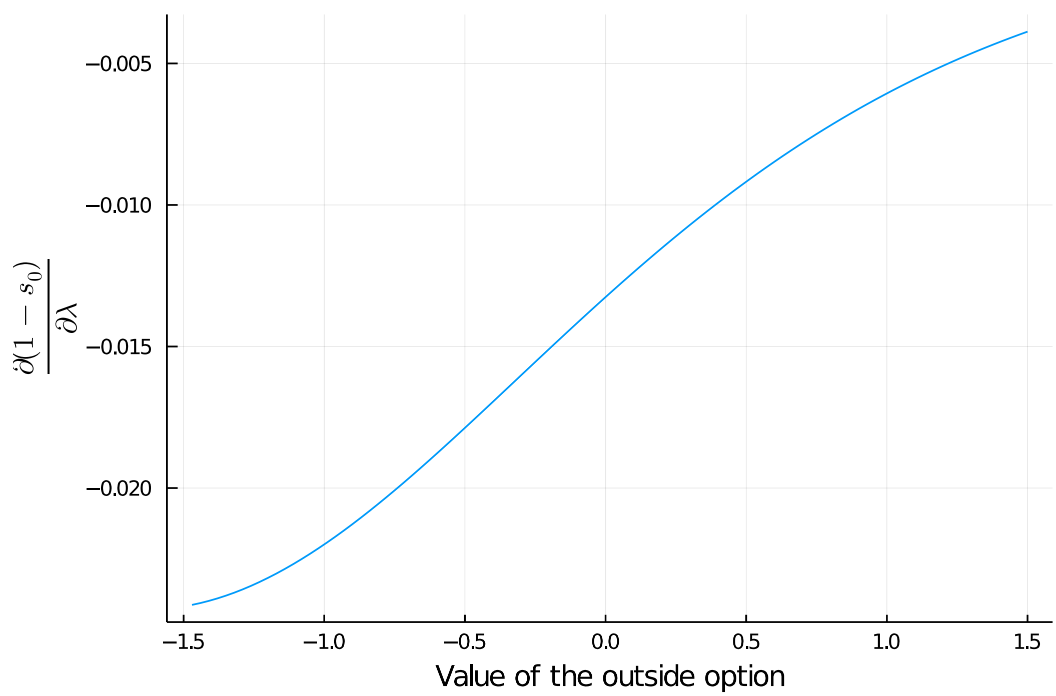
We used the *Julia* language to solve for the equilibrium and compute numerical derivatives. Figure 1 shows the derivatives of the log wage and of the employment-population ratio with respect to λ, as a function of the value of the outside option v_0. As can be seen from the figure, in the calibrated model, the sensitivity of the log wage with respect to changes in common ownership decreases when the utility of the outside option increases. The sensitivity of the employment-population ratio to changes in common ownership also decreases when the utility of the outside option increases.

Figure 1. Sensitivity of Equilibrium Wage and Employment-Population Ratio to Common Ownership Parameter, As a Function of the Value of the Outside Option

(a) Log(Wages per Employee)



(b) Employment-Population Ratio



In the following sections, we empirically examine the relation between common ownership and labor market outcomes and how the estimated effects vary with the value of employees' outside options.

3 Data Description

3.1 Data on Wages and Employment

Data on employee wages and total employment is from the annual average files from the Quarterly Census of Employment and Wages (QCEW). We define a labor market as the interaction between a 4-digit NAICS industry and a February 2013 version of core-based statistical area (CBSA).[3] The NAICS industry codes in QCEW change versions over time, and we harmonize all 4-digit NAICS codes to the 2012 version.[4] This procedure produces a measure of annual wages per employee and total employment at the CBSA$\times$2012 version 4-digit NAICS industry level that is consistent over time. Data on population by age group is from the Surveillance, Epidemiology, and End Results Program of National Cancer Institute (SEER).[5] The original data is available at the county-year level and we aggregate it to the CBSA-year level. We define the working age population as the population with age between 20 and 64. In the empirical analysis, employment-to-population ratio is defined as the ratio of local industry-level total employment to CBSA-level working-age population.

Table 1 reports the summary statistics of the variables in the empirical analysis. In the estimation sample, there are 812,444 local industries with 383 CBSAs and 303 2012 4-digit NAICS industries.[6] Dollars are inflated to 2019. Across local industries and years, the average annual wages per employee is $46,130, and the average employment-to-population ratio at the local

[3] See more detail in QCEW area code guide, available at https://www.bls.gov/cew/classifications/areas/area-guide.htm. The crosswalk between county and metro/micropolitan is available at https://www.bls.gov/cew/classifications/areas/county-msa-csa-crosswalk.htm.

[4] 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 4-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 4-digit NAICS code splits into multiple 2012 codes, then we estimate the payroll or employment in a CBSA$\times$2012 NAICS code$\times$year cell as the original value times the corresponding weight provided in the concordance. The concordance between the 2017 and the 2012 version NAICS is available at https://www.census.gov/eos/www/naics/concordances/concordances.html. If one 2017 NAICS code splits into multiple 2012 codes, then we assign an equal weight to each split, and estimate the payroll or employment in a CBSA$\times$2012 NAICS code$\times$year cell as the original value times the assigned weight.

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

[6] Between 2000 and 2018, employment and wages are missing for around 48% of observations at CBSA$\times$4-digit NAICS level.

industry level is 0.33 percentage points.

Table 1. Summary Statistics

This table reports the (unweighted) summary statistics of variables in the empirical analysis. All variables are at the local industry-year level. Annual pay per employee is in 2019 dollars.

	N	Mean	Std.Dev.	P10	P50	P90
Annual Pay per Employee	812,444	46130.175	27104.495	20081.455	41683.545	75307.125
Employment-to-Population Ratio	812,444	0.327	0.634	0.021	0.143	0.741
Common Ownership (Average λ)	812,444	0.016	0.071	0.000	0.000	0.032
Total Institutional Ownership	812,444	0.093	0.155	0.000	0.010	0.313
TOP 5 Institutional Ownership	812,444	0.035	0.059	0.000	0.004	0.118

3.2 Common Ownership and Institutional Ownership Data

To measure common ownership in each local industry, we combine information on firm-level employment share at the local industry level with data on the institutional ownership at the firm level.

To estimate firm-level employment share at the local industry level, we use establishment-level employment data from Data Axle. Data Axle is a marketing company and provides data on almost every business in the United States and Canada. Between 1999 and 2017, Data Axle on average covers 13.7 million establishments annually, with 11 million establishments surveyed in 1999 and the number increases to 14.8 million in 2017. For each surveyed establishment, Data Axle reports employment, sales, industry, geographic location (longitude, latitude, zipcode, county, and state), and ultimate parent company. The data on establishment-level employment is reliable since it is verified by Data Axle's phone verification process. Data Axle assigns each establishment a unique identifier, 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 QCEW excludes non-employer 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.

The institutional ownership (IO) data at the firm level is from Backus, Conlon and Sinkinson (2021*b*).[7] The authors scraped the IO data from 13F files directly and the data is available between 1999 Q1 and 2017 Q3. We aggregate ownership data to the fund family level for the "Big Three" (BlackRock, Vanguard, and State Street) and Barclays based on the asset managers'

[7] The IO data is available at https://sites.google.com/view/msinkinson/research/common-ownership-data.

names in the data. Combining the employment data from Data Axle and IO data from Backus, Conlon and Sinkinson (2021*b*), we can measure local common ownership in each local industry in a given year. The details are described below.

Suppose there are J_m employing firms in a local industry m. Let ω_j be the employment share for firm j in the local industry's labor market. 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 assume that the proportional control assumption holds so that shareholder s's voting share is equal to its control share. Common ownership in a local industry, λ_m, is then defined as follows:

$$\lambda_m = \sum_{j=1}^{J_m} \left(\sum_{k \neq j} \frac{\omega_j \omega_k}{1 - \omega_j} \times \lambda_{j,k} \right), \tag{3.1}$$

where $\lambda_{j,k}$ measures the connection between any two firms j and k via common ownership and is equal to $\frac{\sum_{\forall s} \beta_{js}\beta_{ks}}{\sum_{\forall s} \beta_{js}\beta_{js}}$. If either firm j or k is not publicly traded or not held by any institutional investors, then $\lambda_{j,k} = 0$. Institutional ownership data is at the quarterly level, so we first calculate the local industry common ownership measure in each quarter and then take the simple average across all quarters in a year to construct the annual measure.

We also measure total IO and IO of the top five institutional investors at the local industry level in a similar fashion. Specifically, local industry total IO (IO_m) and top five IO (IO_m^{Top5}) are defined as follows. In a local industry, if there is no publicly traded firm or all the firms are not held by any institutional investors, then we set IO_m and IO_m^{Top5} as zeros.

$$IO_m = \sum_{j=1}^{J_m} \omega_j \times IO_j \tag{3.2}$$

$$IO_m^{Top5} = \sum_{j=1}^{J_m} \omega_j \times IO_j^{Top5} \tag{3.3}$$

Table 1 reports the summary statistics of λ_m, IO_m, and IO_m^{Top5}. In our sample, around 63% of local industries (510,331 local industries) have zero local common ownership and the average common ownership across local industry-years is 1.6 percentage points. The average local total IO and top five IO are 9.3 and 3.5 percentage points, respectively.

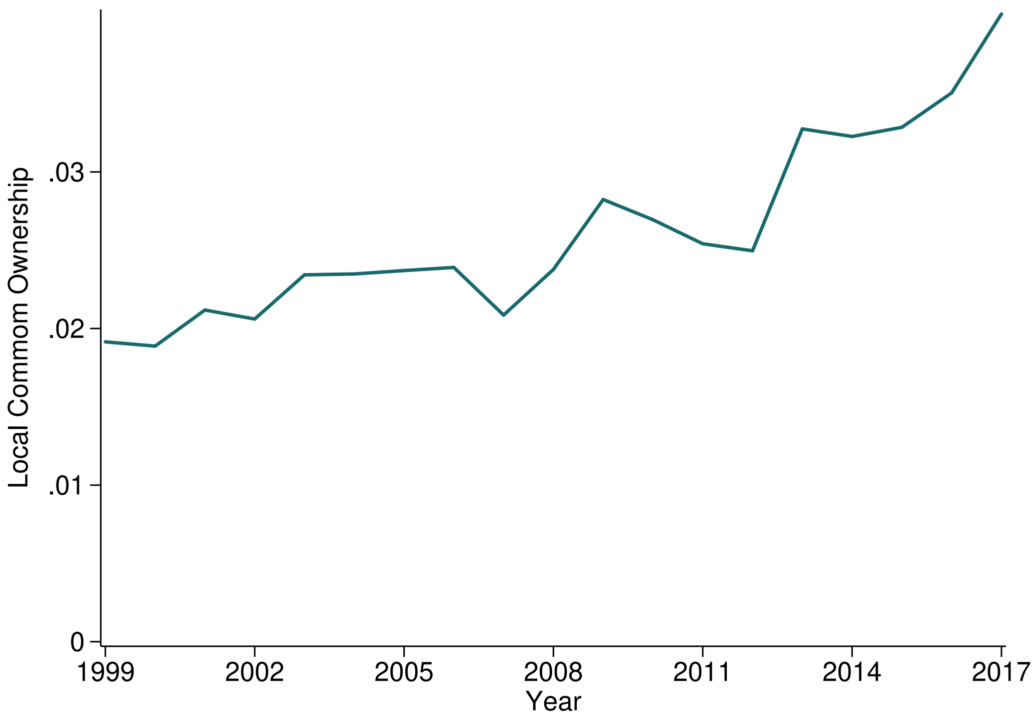
Figure 2 reports the trend of local industry-level common ownership between 1999 and 2017. In each year, we calculate the employment-weighted average of the λs across local industries.[8] The figure shows that common ownership at the local industry level has trended up over the period 1999-2017. In 1999, the average local common ownership is 0.019 and it more

[8]The employment is based on data from Data Axle.

than doubles to 0.04 in 2017.

Figure 2. Common Ownership in Local Industry Labor Markets: 1999-2017

We calculate the employment-weighted average local common ownership across local industries in each year.



4 Empirical Specifications

We empirically study the effects of common ownership in labor markets on average annual wages per employee and employment using two approaches: a panel regression approach using both OLS and 2SLS regressions of labor market outcomes on common ownership measures, and an event study based on the acquisition of Barclays BGI by BlackRock in 2009.

4.1 Panel Regressions

We start by estimating the relation between common ownership and employee wages or employment-to-population ratio at the local industry level using OLS. We study how changes in local common ownership relate to changes in labor market outcomes in a local industry by including local industry and year fixed effects. Specifically, we estimate the following equation:

$$y_{ci,t} = \alpha\lambda_{ci,t-1} + \beta X_{ci,t-1} + \gamma_{ci} + \delta_t + \varepsilon_{ci,t} \tag{4.1}$$

c, i, and t index for CBSA, 4-digit NAICS industry, and year, respectively. $y_{ci,t}$ is the natural logarithm of annual wages per employee or the employment-to-population ratio in local industry (c,i) in year t. $\lambda_{ci,t-1}$ is common ownership in a local industry (c,i) in year t-1. $X_{ci,t-1}$ is a vector of control variables in a local industry (c,i) measured at year t-1. Specifically, we follow Falato, Kim and von Wachter (2021) and control for total institutional ownership (IO) and ownership of the largest five institutional investors (IO^{Top5}) at the local industry level. The variable γ_{ci} represents local industry fixed effects, which helps to control for any time-invariant unobserved characteristics at the local industry 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 allow for clustering at the local industry level.

In the first specification, we only include local industry and year fixed effects. We then further control for the average institutional ownership and average ownership of top five institutional investors in a local industry. Finally, we run a third specification that further controls for CBSA$\times$year fixed effects, absorbing any shock in a CBSA in a given year.

Identification relies on assumptions of 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 industry experiences a negative shock to labor productivity, then employee wages would decrease. At the same time, it might induce exits of privately-held firms, driving 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 industry 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 wages and local common ownership simultaneously, resulting in an upward bias of the OLS estimate. Assuming that the local industry's labor market is not competitive and firms face upward-sloping labor supply curves, then the direction of the bias of OLS estimate on employment-to-population ratio would be the same as the direction of the bias of OLS estimate on wages.

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

We again index CBSA and 4-digit NAICS industry by c and i, respectively, and denote the number of CBSAs 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).

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 labor market outcomes and local common ownership could be correlated across CBSAs. For example, suppose that an industry experiences a negative shock that decreases employee wages across the nation and also leads some privately-held firms to exit in some CBSAs. Mechanically, this shock would induce an increase in the equally-weighted version of local common ownership measure in these local industries 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 industry level.

4.2 BlackRock-BGI Event Study

To further mitigate concerns about the endogeneity concerns in the IV analysis, we exploit a natural experiment generated by the acquisition of a large asset manager, Barclays Global Investors (BGI), by another large asset mangaer, Blackrock (BLK). The acquisition was announced in 2009Q2 and was completed in 2009Q4. This acquisition changed the degree of local common ownership differently but predictably in each local industry, making it an appealing source of variation to leverage. In each market, the acquisition increased local common ownership more when BLK and BGI each owned a larger share of local firms. If only BLK, only BGI, or neither owned a local firm, this caused no change in local common ownership. This interaction between the merging shareholders' ownership shares and the firms' employment shares generates a lot of variations in its impacts on local common ownership across local industries. Others have exploited this acquisition to study the common ownership effects on product markets, including Azar, Schmalz and Tecu (2018).

Following Azar, Schmalz and Tecu (2018), we construct a measure of predicted acquisition-induced change in local common ownership for each local industry using pre-acquisition ownership and employment information. Specifically, for each local industry in 2008, we first calculate the local industry common ownership using the realized ownership information in 2009 Q1 and then calculate the same measure assuming that BLK and BGI were already merged. The difference between the hypothetical and the realized local industry common ownership is the implied change in common ownership, $\Delta\lambda$.

To estimate the treatment effects of the BLK-BGI acquisition on wages per employee and employment-to-population ratio at the local industry level, we employ a synthetic control method that can be applied to the case with high-dimensional, micro-level data developed in Robbins, Saunders and Kilmer (2017). Compared to the canonical synthetic control method in Abadie, Diamond and Hainmueller (2010), the major advantage of this newly developed method is that it is feasible to construct a synthetic control unit that simultaneously matches across multiple time-varying outcomes and time-invariant covariates.

To implement the synthetic control method, we require a balanced panel for each local industry from 1999 to 2017. We define treated and control local industries based on $\Delta\lambda$s. In our sample, there are 8,749 local industries in which $\Delta\lambda$s are equal to zero and 6,095 local industries in which $\Delta\lambda$s are strictly positive. There are also 246 local industries in which $\Delta\lambda$s are strictly negative and they are excluded from our estimation sample for implementing the synthetic control method. Among all local industries with strictly positive $\Delta\lambda$s, the sample median is 0.0022 percentage points and the 75th, 90th, 99th percentiles are 0.153 percentage points, 0.477 percentage points, and 1.976 percentage points, respectively. A local industry is defined to be treated if its $\Delta\lambda$ is above the sample median of strictly positive $\Delta\lambda$s, and to be a control local industry if its $\Delta\lambda$ is below the sample median of strictly positive $\Delta\lambda$s or its $\Delta\lambda$ is equal to zero. There are 3,047 treatment local industries and 11,797 control local industries in our sample.

We then apply the method developed in Robbins, Saunders and Kilmer (2017) to our sample. Specifically, during the 10 years before the treatment (between 1999 and 2008), we match the trends of three outcome variables, common ownership measure (λ), the natural logarithm of wagers per employee, and employment-to-population ratio, as well as the pre-treatment average of employment distribution (10th, 25th, median, 75th, and 90th percentiles) and employment share of publicly traded firms. Matching on these covariates would help control for the effects of firm composition on labor market outcomes in a local industry.

The following discussions on the details of the synthetic control method are based on Robbins, Saunders and Kilmer (2017). This method aims to calculate a set of weights on control local industries, $(\omega_1, \omega_2, ..., \omega_{N_0})$, such that for each year $t \in (1999, 2000, ..., 2008)$ the following equations hold:

$$\sum_{j \in Control} \omega_j \times y_{jt} = \frac{1}{N_1} \sum_{i \in Treatment} y_{it}$$
$$\sum_{j \in Control} \omega_j \times z_j = \frac{1}{N_1} \sum_{i \in Treatment} z_i$$
$$\text{subject to} \sum_{j \in Control} \omega_j = 1$$

where y_{jt} represents any of the three time-varying outcome variables and z_j represents any of the six time-invariant pre-treatment average of the covariates. Here, N_1 and N_0 represent the number of treated and control local industries, respectively.

Given the solution vector $(\omega_1^*, \omega_2^*, ..., \omega_{N_0}^*)$ that satisfies the above system of equations, the estimated treatment effect on treated for each outcome y in each year t is given as:

$$\hat{\tau}_{yt}^* = \frac{1}{N_1} \sum_{i \in Treatment} y_{it} - \sum_{j \in Control} \omega_j^* \times y_{jt}$$

To draw inference, we perform a permutation test as in Abadie, Diamond and Hainmueller (2010). In particular, we perform 1,000 placebo tests and, in each placebo test, we estimate the placebo estimated treatment effect on the treated in each year for each outcome. To form the 95% confidence interval (CI) of the point estimation in each year, we need to solve values that cannot be rejected as being equal to $\hat{\tau}_{yt}^*$ at the 5% level. In other words, the confidence interval includes the values η satisfying $0.025 \leq F(\hat{\tau}_{yt}^* - \eta) \leq 0.975$, where $F(\cdot)$ is the empirical CDF of the placebo estimates. Therefore, the lower and upper bounds of the 95% CI are $\hat{\tau}_{yt}^* -$

$F^{-1}(0.975)$ and $\hat{\tau}^*_{yt} - F^{-1}(0.025)$, respectively.

5 Results

5.1 Panel Regressions

We first report the estimated effects of common ownership on employee wages in Table 2. Columns (1)-(3) report OLS estimates. In column (1), we only include local industry and year fixed effects. The estimated coefficient on *Common Ownership* is -0.038 and is statistically significant at 1% level. The estimated effect implies that a one-standard-deviation increase in local common ownership (0.071) is associated with a 0.27% (=0.071*0.038) decrease in annual wages per employee. This is $125 per year given the sample mean of $46,130. In column (2), we control for total institutional ownership and top five institutional ownership at the local industry level. The results are robust and the estimated coefficient becomes to -0.047. In column (3), we further control for CBSA×year fixed effects to control for any shock at the CBSA × year level. The results are also robust.

Table 2. Common Ownership and Employee Wages

The instrumental variable for *Common Ownership* is the average of the equally-weighted *Common Ownership* for the same industry in all other CBSAs. The instrumental variables for *Institutional Ownership* and *Top 1 Institutional Ownership* are defined analogously. Standard errors are clustered at the local industry level. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Common Ownership	-0.038***	-0.047***	-0.047***	-0.126***	-0.184***	-0.185***
	[0.007]	[0.007]	[0.007]	[0.016]	[0.016]	[0.016]
Institutional Ownership		0.012	0.011		0.060*	0.066**
		[0.009]	[0.009]		[0.032]	[0.032]
Top 5 Institutional Ownership		0.000	0.000		0.160*	0.151*
		[0.022]	[0.021]		[0.091]	[0.089]
Local Industry FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓		✓	✓	
CBSA×Year FEs			✓			✓
Kleibergen-Paap rk Wald F-stat				3898.7991	1724.8227	1731.8062
Adjusted R^2	0.921	0.921	0.922			
N	812,444	812,444	812,444	812,444	812,444	812,444

Columns (4)-(6) report 2SLS estimates. Across all the columns, the first stage Kleibergen-

Paap F-statistic is large, suggesting our instrumental variable is not weak. The magnitudes of the estimated common ownership effects are larger than the ones from OLS, suggesting that our local common ownership is negatively correlated with unobserved factors that are positively correlated with employee wages. Based on the estimations in column (6), our results show that a one-standard-deviation increase in local common ownership (0.071) is associated with a 1.3% (=0.071*-0.185) decrease in annual wages per employee, or $600 per year.

We now turn to the estimated effects of common ownership on employment-to-population ratio, which is defined as the ratio of local industry-level employment to CBSA-level working age population. The results are reported in Table 3. OLS estimates are reported in columns (1)-(3) and 2SLS estimates are reported in columns (4)-(6). Across all specifications, we find that an increase in local common ownership is associated with a lower employment-to-population ratio in a local industry. The magnitudes of 2SLS estimates are larger than the ones of OLS estimates. For example, estimations in column (3) implies that a one-standard-deviation increase in local common ownership is associated with a 0.46% (=0.071*-0.021/0.327) decreases in employment-to-population relative to the sample mean; while 2SLS estimates in column (6) imply that a one-standard-deviation increase in common ownership is associated with a 6.6% (=0.071*-0.306/0.327) decrease in employment-to-population ratio relative to the sample mean.

Furthermore, 2SLS estimates also suggest that IO and IO^{Top5} have larger effects on employment-to-population ratio than on wages per employee, which is consistent with the results in Falato, Kim and von Wachter (2021). For example, based on the results in column (6) in both Tables 2 and 3, a one-standard-deviation increase in IO (0.155) is associated with a 1.02% (=0.155*0.066) increase in annual wages per employee but is associated with a 9.95% (=0.155*0.21/0.327) increase in employment-to-population ratio. For IO^{Top5}, a one-standard-deviation increase is estimated to be associated with a 0.89% (=0.059*0.151) increase in wages per employee and a 8.03% (=0.059*-0.445/0.327) decrease in employment-to-population ratio.

Overall, the OLS and 2SLS estimates in Table 2 and Table 3 are consistent with theoretical predictions in Proposition 1, that common ownership in a local labor market reduces wages and employment probabilities.

5.2 BlackRock-BGI Event Study

We report the synthetic control estimate in Figures 3 and 4.[9] In each figure, each dot represents the estimated treatment effect on treated. The lines around each dot represent the constructed 95% CI.

We start with the estimated effect of the BLK-BGI acquisition on local common ownership

[9]We use the R package "microsynth" to implement the synthetic control method.

Table 3. Common Ownership and Employment-to-Population Ratio

The instrumental variable for *Common Ownership* is the average of the equally-weighted *Common Ownership* for the same industry in all other CBSAs. The instrumental variables for *Institutional Ownership* and *Top 1 Institutional Ownership* are defined anagalously. Standard errors are clustered at the local industry level. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Common Ownership	-0.018	-0.021*	-0.021*	-0.246***	-0.305***	-0.306***
	[0.011]	[0.011]	[0.011]	[0.024]	[0.026]	[0.026]
Institutional Ownership		0.000	-0.000		0.207***	0.210***
		[0.009]	[0.009]		[0.046]	[0.046]
Top 5 Institutional Ownership		0.014	0.014		-0.442***	-0.445***
		[0.024]	[0.024]		[0.143]	[0.143]
Local Industry FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓		✓	✓	
CBSA $\times$ Year FEs			✓			✓
Kleibergen-Paap rk Wald F-stat				3898.7991	1724.8227	1731.8062
Adjusted R^2	0.948	0.948	0.948			
N	812,444	812,444	812,444	812,444	812,444	812,444

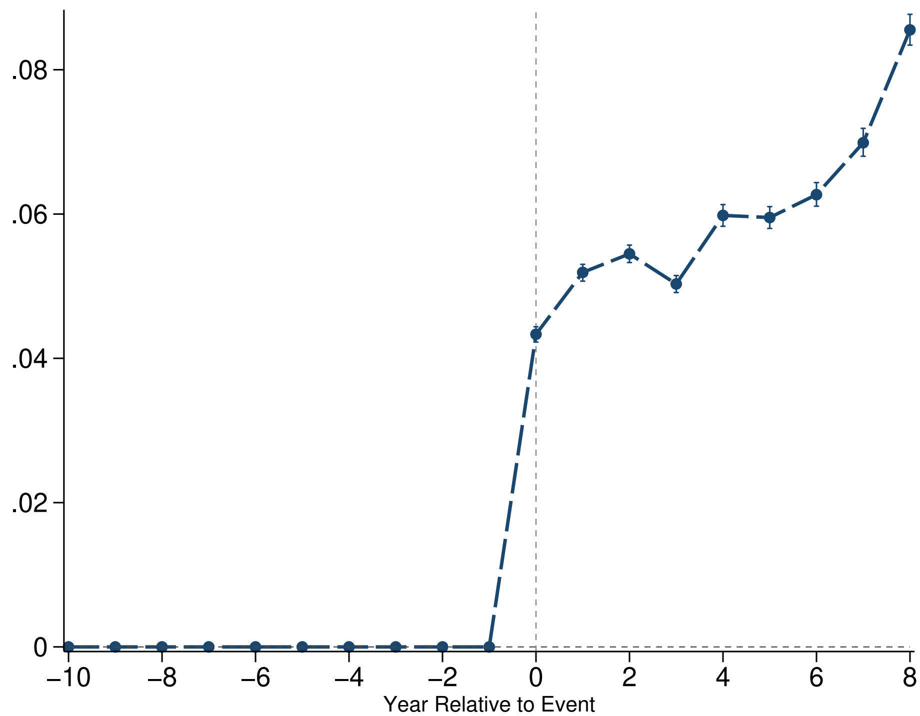
and the results are reported in Figure 3. Our estimates show evidence that the BLK-BGI acquisition leads to an increase in local common ownership in treated local industries compared to synthetic control local industries. Between 1999 and 2008, the levels of local common ownership in treated and synthetic control local industries are very-well matched, understandable given the large pool of control markets available to match each treatment market's pre-trends. Since the acquisition between BLK and BGI, the trajectories of local common ownership in treated and synthetic control local industries start to diverge. Compared to the synthetic control, local common ownership measures in treated local industries increase 6.2 percentage points between 2010 and 2017 with 95% CI of [0.061, 0.063].

The estimated treatment effect has been increasing over time. In 2009, the estimated treatment effect on local common ownership is 4.3 percentage points and, by the end of 2017, the estimated treatment effect increases to 8.6 percentage points. The estimated treatment effect on treated in each year during the post-acquisition period is statistically significant at 5% level.

We then estimate the effects of the BLK-BGI acquisition on the natural logarithm of annual wages per employee and the results are reported in panel (a) of Figure 4. Again, the algorithm successfully matches the levels of annual wages per employees in treated and synthetic control local industries in each year between 1999 and 2008. During years 2009 and 2010, the estimated

Figure 3. Effect of BlackRock-BGI Acquisition on Local Industry Labor Market Common Ownesrship (λ).

The lines around point estimations represent 95% CIs, which are constructed based on 1,000 permutation tests.



treatment effects on the natural logarithm of annual wages per employees are small and they are 0.47% and 0.06%, respectively. Since year 2011, the magnitudes of estimated treatment effects on the natural logarithm of annual wages per employees start to increase and all the point estimations are statistically significant at 5% level. On average, the estimated treatment effect on the natural logarithm of annual wages per employees is -2.9% between 2010 and 2017 with 95% CI of [-0.035, -0.024].

Finally, we estimate the treatment effect of the BLK-BGI acquisition on employment-to-population ratio in a local industry. We report results in panel (b) of Figure 4. During the pre-acquisition period, the levels of employment-to-population ratio in treated and synthetic control local industries are again well matched by the estimator. During the post-acquisition period, our results show that employment-to-population ratio in treated local industries starts to decrease since 2011 compared to the synthetic control local industries. The point estimation in each year is statistically significant at 5% level and the magnitudes of estimated treatment effects are increasing over time. The average estimated treatment effect of the BLK-BGI acquisition on employment-to-population ratio is -0.038 percentage points between 2010 and 2017 with the 95% CI of [-0.045 percentage points,-0.031 percentage points]. Among all treated local industries, the average employment-to-population ratio is 0.81 percentage points between 1999 and 2008, therefore, our estimation represents a 4.7% decrease relative to the sample mean of pre-acquisition employment-to-population ratios in treated local industries.

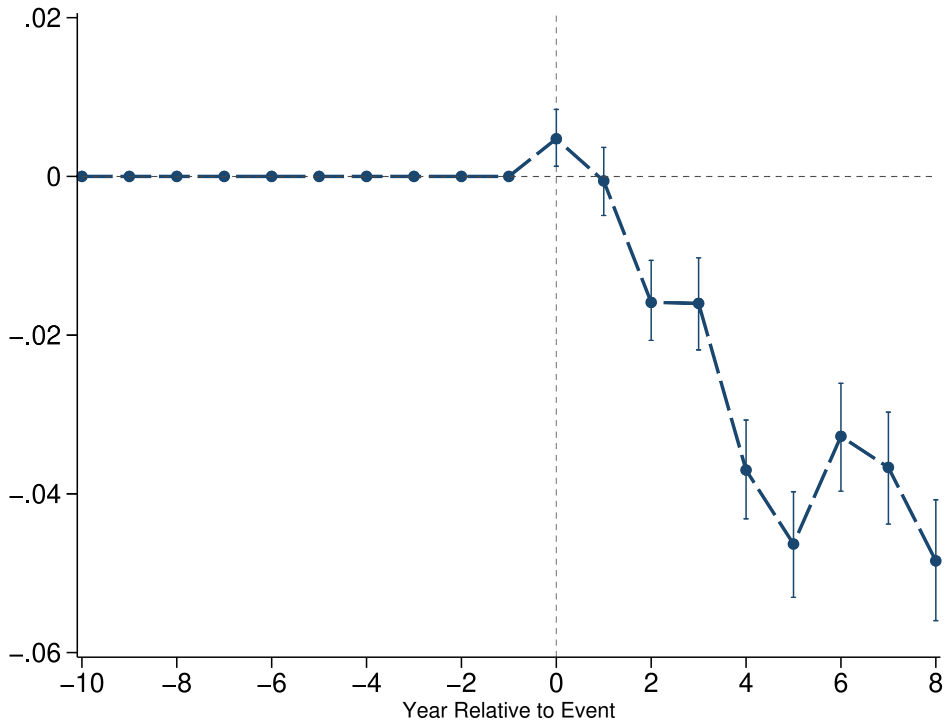
In 2017, the estimated treatment effect of the BLK-BGI acquisition is 8.6 percentage points for λ, -4.9% for employee wages, and -0.073 percentage points for employment-population ratio. This implies an average wage semielasticity with respect to λ of -0.57 (which in turn implies that a one-percentage-point increase in common ownership decreases wages by 0.57%). Given that the average pre-treatment level of employment-population ratio is 0.81 percentage points, our estimates imply an average employment-to-population semielasticity with respect to λ of -1.05 (which in turn implies that a one-percentage-point increase in common ownership decreases the employment-to-population ratio by 1.05%). If we extrapolate these numbers to the whole economy in 2017 with the level of common ownership reported in Figure 2 (0.04), then this exercise would imply that wages are 2.28% lower and the employment-to-population ratio is 4.2% lower, relative to a counterfactual of no common ownership.

Overall, our synthetic control estimates show that the BLK-BGI acquisition led to increases in local common ownership in a local industry and we simultaneously observe a decrease in both the natural logarithm of wages per employee and the employment-to-population ratio. Such evidence is consistent with the theoretical predictions in Proposition 1.

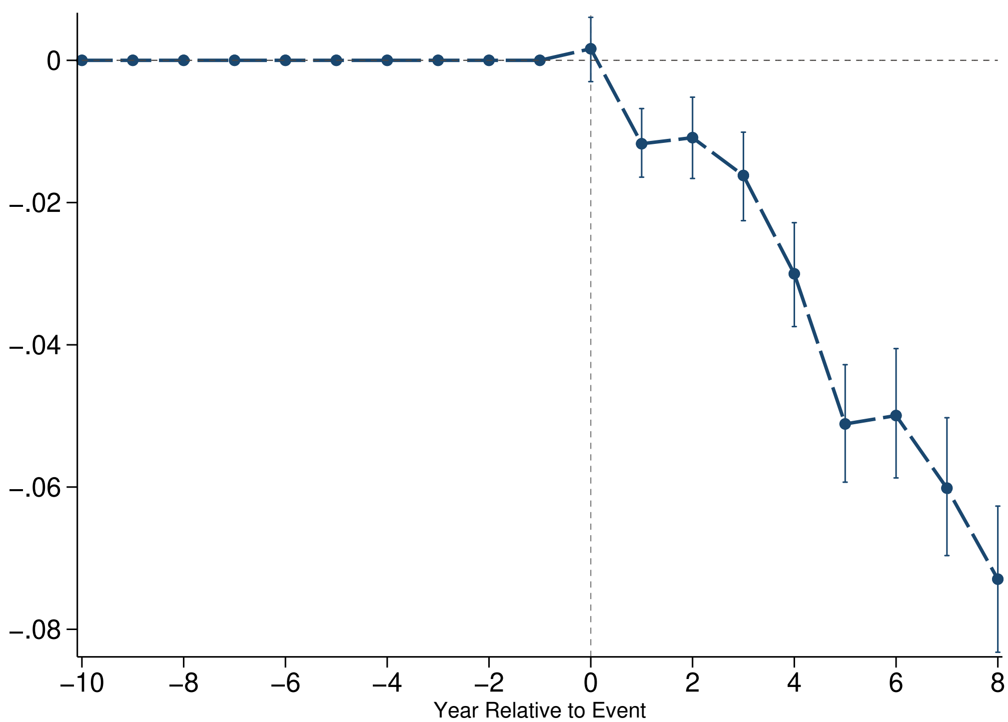
Figure 4. Effect of BlackRock-BGI Acquisition on Local Industry Labor Market Wages and Employment.

The lines around point estimations represent 95% CIs, which are constructed based on 1,000 permutation tests.

(a) Log(Wages per Employee)



(b) Employment-Population Ratio



6 Heterogeneity

The model in Section 2 predicts that common ownership effects on labor market outcomes are heterogeneous. For both employee wages and employment-to-population ratio, our model predicts that the effect of common ownership is larger (in absolute value) when the value of employees' outside options is lower. In this section, we empirically test these predictions.

We measure employees' outside options in three ways. First, we proxy for the value of employees' outside options by the average pre-acquisition macroeconomic conditions, including unemployment rate and personal income per capita, at the CBSA level. The rationale of this approach is that if the pre-acquisition macroeconomic conditions in a CBSA are better, then employees in a certain local industry would have more opportunities to work in other industries. As a result, the magnitudes of the estimated treatment effects on local industry-level wages and employment are expected to be larger (smaller) if unemployment rate is higher (lower) or personal income per capita is lower (higher). Data on unemployment rate comes from the Local Area Unemployment Statistics program (LAUS) of the Bureau of Labor Statistics (BLS).[10] The original data is at the county-year level. We aggregate the data to the CBSA-year level and estimate the unemployment rate as the number of unemployed divided by the size of labor force. Data on personal income per capita comes from the Regional Economic Accounts of the Bureau of Economic Analysis (BEA).[11] We again aggregate the county-year level personal income and population data to CBSA-year level and then estimate the personal income per capita at the CBSA-year level.

Second, we proxy the value of employees' outside options by the average pre-acquisition population density at the CBSA level. This measure is motivated by the evidence in Azar, Marinescu and Steinbaum (2020). Specifically, Azar, Marinescu and Steinbaum (2020) shows that the effect of local labor market concentration has a more negative effect on wages for less-populated commuting zones. Such evidence suggests that employees in less populated areas tend to have fewer outside options and the effect of the BLK-BGI acquisition is expected to have a larger impact on wages or employment-to-population ratio. Data on population and land area in a county comes from the U.S. Gazatteer Files.[12] Before (including) 2000, the data is available every other ten years and since year 2012, the data is available every year. In our setting, we use the data in the year 2000 to construct the measure of population density during the pre-acquisition period. Specifically, We aggregate both county-level population and land

[10]The data is available at https://www.bls.gov/lau/.

[11]The data is available at https://www.bea.gov/data/income-saving/personal-income-county-metro-and-other-areas.

[12]The data is available at https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.html.

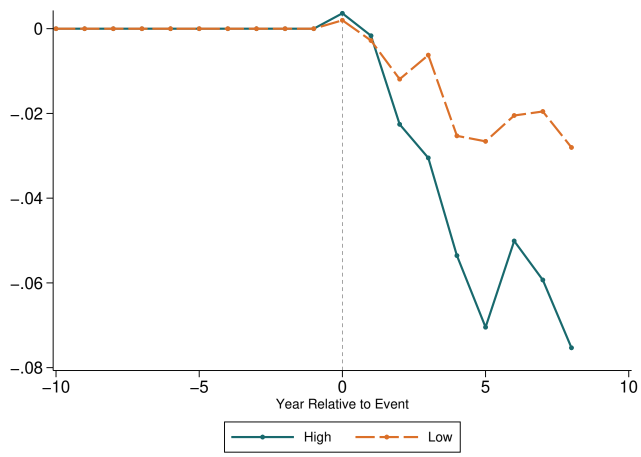
area data to the CBSA level and estimate population density as population per square miles.

Third, we use the enforceability of non-compete clauses at the CBSA level to proxy for the value of employees' outside options. When employees are bounded by noncompete clauses, their ability to move to employers in the same industry within a geographic area (usually a state) becomes limited (Garmaise, 2011). As a result, in order to get around the restrictions imposed by non-competes after separating from the current employers, these employees would have to join new employers in other industries or geographic areas. In either case, the cost associated with searching for new employers would increase and this would decrease the value of outside options, leading to a lower labor mobility (Johnson, Lavetti and Lipsitz, 2021). Therefore, we expect the estimated treatment effects of the BLK-BGI acquisition on wages or employment-to-population ratio to be more negative when noncompete clauses are more enforced at the CBSA level. The enforceability of noncompete clauses is determined at the state level and we estimate the enforceability at the CBSA level as the population-weighted of state-level enforceability index, obtained from Marx (forthcoming).

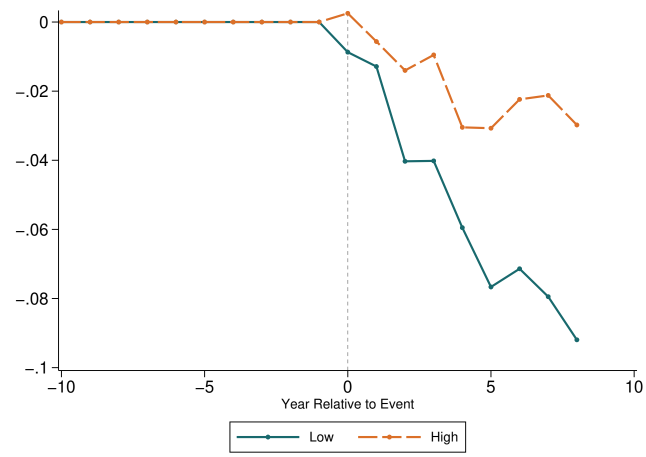
Among all treated local industries, we calculate the average of each measure of outside options value between 1999 and 2008 at the CBSA level and split the CBSAs of treated local industries based on the sample median. We then re-estimate the treatment effect for treated local industries in CBSAs where employees have high and low value of outside options separately. The results on wages and employment-to-population ratio are reported in Figures 5 and 6, respectively.

Figure 5. Heterogeneity Effects of BLK-BGI Acquisition on Local Industry Labor Market Wages

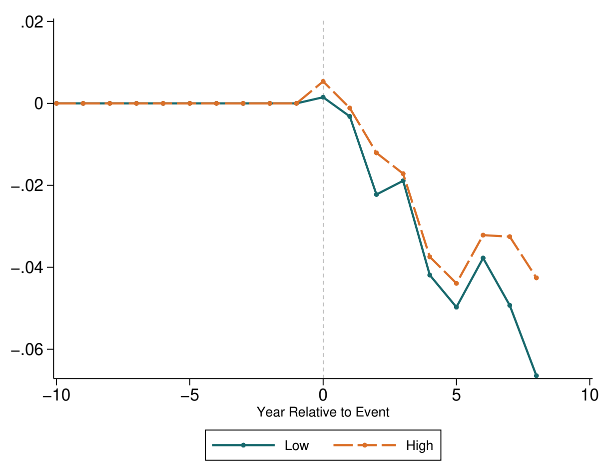
(a) Unemployment Rate



(b) Personal Income per Capita



(c) Population Density



(d) Non-compete Index

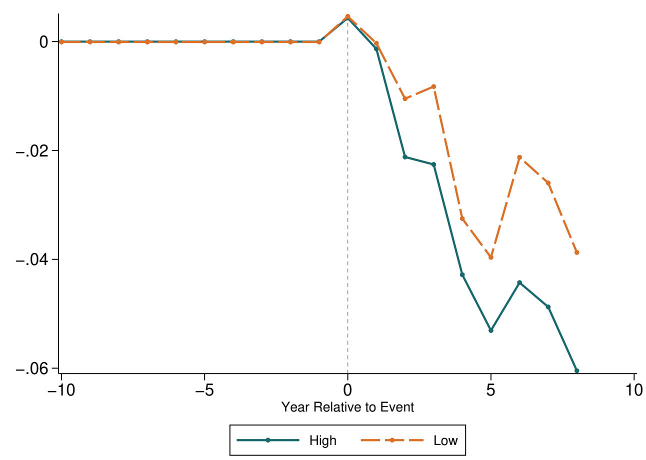
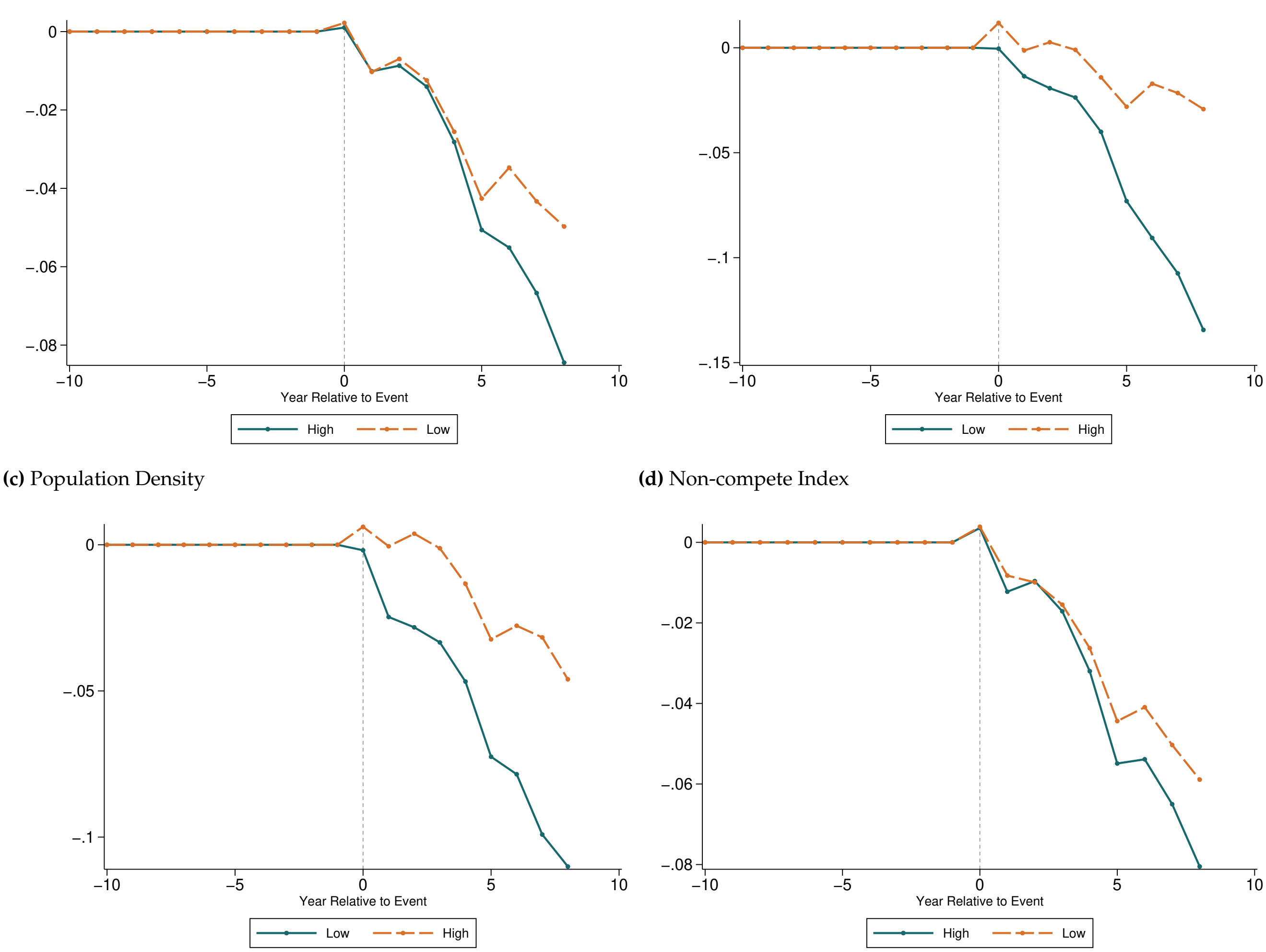


Figure 6. Heterogeneity Effects of BLK-BGI Acquisition on Local Industry Labor Market Employment



(a) Unemployment Rate **(b)** Personal Income per Capita **(c)** Population Density **(d)** Non-compete Index

In the top panel of Figures 5 and 6, we report the estimated treatment effects by the average unemployment rate and personal income per capita during the pre-acquisition period. The estimations show that, compared to the synthetic control group, BLK-BGI acquisition on average leads to a 4.5% decrease in wages per employee and 0.040 percentage points in employment-to-population ratio in treated local industries with higher pre-acquisition unemployment rates at the CBSA level; in contrast, the estimated average treatment effects on wages and employment-to-population ratio are -1.8% and -0.028 percentage points, respectively, for local industries with lower pre-acquisition CBSA-level unemployment rates.

The results are qualitatively similar if we split the sample by pre-acquisition average CBSA-level personal income per capita. Specifically, for treated local industries with lower pre-acquisition CBSA-level income per capita, the estimated treatment effects are wages and employment-to-population ratio are -5.9% and -0.063 percentage points, respectively; But for treated local industries with higher CBSA-level income per capita during the pre-acquisition period, the estimated treatment effects on wages per employee and employment-to-population ratio are -2.0% and -0.014 percentage points, respectively.

In panels (c) of Figures 5 and 6, we report the estimated treatment effects by the population density of year 2000 at the CBSA level. Our results show that the estimated treatment effects of the BLK-BGI acquisition on wages and employment-to-population ratio are more negative for treated local industries in CBSAs with lower population densities. For the estimated treatment effect on employment-to-population ratio, the contrast between treated local industries in CBSAs with lower and higher population densities is more evident. Our results suggest that the BLK-BGI acquisition leads to 0.062 percentage points decrease in employment-to-population ratio for local industries in less populated CBSAs while the estimated effect is only -0.019 percentage points for local industries in more populated CBSAs. The estimated effect of the BLK-BGI acquisition on wages is also more negative for local industries in CBSA with lower pre-acquisition population densities. The difference in the estimated average treatment effects across two types of treated local industries is much smaller (-3.6% vs. -2.7%). However, the gap in the estimated treatment effects across these two types of treated local industries widens over time. Between 2010 and 2015, the average difference in the estimated treatment effects across these two types of local industries is only 0.5%. But during the year 2016, the gap becomes 1.68% and it increases to 2.39% during the year 2017.

In panels (d) of Figures 5 and 6, we report the estimated treatment effects by the average enforceability of non-competes at CBSA level during the pre-acquisition period. The results show that the estimated treatment effects on wages and employment-to-population ratio are more negative for treated local industries where non-competes are more enforced. On average, the BLK-BGI acquisition leads to a 3.7% (2.2%) decrease in wages per employee and 0.041 (0.032) percentage points decrease in employment-to-population ratio for treated local industries in which non-competes are more (less) enforced. For both wages and employment-to-population ratio, the difference in the estimated effects between these two groups of treated local industries becomes larger since year 2015. By the end of year 2017, the results show that, relative to pre-acquisition period, the BLK-BGI acquisition leads to a 6.0% decrease in wages per employee and 0.08 percentage points decrease in employment-to-population ratio in treated local industries where non-competes are more enforced; For local industries in which non-competes are less enforced, wages per employee and employment-to-population are estimated to decrease by 3.9% and 0.059 percentage points, respectively.

Overall, the results in Figures 5 and 6 are consistent with our expectations, that is, the estimated effects of the BLK-BGI acquisition on employee wages and employment-to-population ratio are more negative for local industries in CBSAs in which employees' outside options value is lower.

7 Conclusion

In recent decades, several macroeconomic trends in the United States stand out: (i) the rise of institutional ownership of US firms, (ii) the consequent rise of common ownership, (iii) the stagnation of employee wages relative to productivity (Bivens and Mishel, 2015), and (iv) a reversal of growth in the employment-to-population ratio (Abraham and Kearney, 2020). Although sensible theory predicts a negative effect of common ownership on wages per employee and employment-to-population ratio, and some studies (Goshen and Levit, 2021; Steinbaum, 2021; Azar and Vives, 2019, 2021*a*) argue that rising common ownership could have contributed downward pressure to labor demand, little is known empirically about whether and how common ownership affects labor market outcomes.

In this paper, we contribute to the literature by measuring common ownership at the local industry level and providing the first empirical evidence on the effects of common ownership on labor market outcomes. We use two empirical approaches to generate new evidence on the labor market effects of common ownership. Consistent across both methods, our results suggest that wages per employee and employment-to-population ratio in a local industry tend to decrease after experiencing an increase in local common ownership. Further analysis also suggests that the estimated effects are more negative for local industries in which the value of employees' outside options is lower.

The policy implications of anticompetitive effects of common ownership in labor markets are complex. Legal scholars have mostly analyzed the antitrust implications of horizontal shareholding in product markets (Elhauge, 2015; Baker, 2015; Posner, Scott Morton and Weyl, 2017; Rock and Rubinfeld, 2020; Posner, 2021), as well as labor market power (Marinescu and Hovenkamp, 2019; Krueger and Posner, 2018; Naidu and Posner, 2021). But what are the implications of incorporating both labor market power and the ownership structure of the industries into their analysis? One potential approach would be tackling the issue directly by breaking up large common owners. However, it is important to note that there are trade-offs from a social point of view as low-cost index funds save costs for retail investors compared to more expensive actively managed funds.

It is at least somewhat reassuring that, on average, common ownership in U.S. labor markets is quite low compared to the level in, say, airlines and banks. At the same time, however, common ownership is high in many local industrial labor markets and policymakers should consider how to mitigate the problem. The heterogeneity results suggest that, even if common ownership is not tackled directly, policies that improve workers' outside options, such as maintaining a low unemployment rate and banning non-compete clauses may have the added benefit of mitigating the anti-competitive effects of common ownership in labor markets.

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Appendix

A Proofs

Proof of Proposition 1

First, note that the derivatives of the equilibrium wage and equilibrium employment-population ratio are related to the derivative of the markdown with respect to lambda.

$$\frac{\partial \log(w^*)}{\partial \lambda} = -\frac{\mu^*}{1+\mu^*} \times \frac{\partial \log \mu^*}{\partial \lambda}. \tag{A.1}$$

$$\frac{\partial (1-s_0^*)}{\partial \lambda} = -\alpha s_0^*(1-s_0^*) \times \frac{\mu^*}{1+\mu^*} \times \frac{\partial \log \mu^*}{\partial \lambda}. \tag{A.2}$$

The derivative of the log markdown with respect to lambda is

$$\frac{\partial \log \mu^*}{\partial \lambda} = \frac{\alpha}{\rho}\mu^* \left\{ \frac{\partial (1-s_0^*)}{\partial \lambda} H\rho + (1-\rho s_0^*)\left(1-\frac{1}{J}\right) \right\}$$

$$\frac{\partial \log \mu^*}{\partial \lambda} = \frac{\alpha}{\rho}\mu^* \left\{ -\alpha s_0^*(1-s_0^*) \times \frac{\mu^*}{1+\mu^*} \times \frac{\partial \log \mu^*}{\partial \lambda} H\rho + (1-\rho s_0^*)\left(1-\frac{1}{J}\right) \right\}$$

Solving for $\frac{\partial \log \mu^*}{\partial \lambda}$, we obtain

$$\frac{\partial \log \mu^*}{\partial \lambda} = \frac{\frac{\alpha}{\rho}\mu^*(1-\rho s_0^*)\left(1-\frac{1}{J}\right)}{1+\frac{\alpha}{\rho}\mu^* \alpha s_0^*(1-s_0^*)\frac{\mu^*}{1+\mu^*}H\rho} > 0. \tag{A.3}$$

Since the signs of the derivatives of the log wage and of the employment-population ratio with respect to λ are the opposite of that of the markdown, the signs of those derivatives are negative.

□