Local Labor Market Concentration and Capital Structure Decisions

John (Jianqiu) Bai, Massimo Massa, Chi Wan, and Yan Wang*

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* John (Jianqiu) Bai is from the finance group at D'Amore-McKim School of Business, Northeastern University, 360 Huntington Ave, Boston, MA, 02115; Email: j.bai@northeastern.edu; Phone: 617-373-6247. Massimo Massa is from INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France; Email: massimo.massa@insead.edu; Tel: 33-1-60724481; Chi Wan is from the College of Management, University of Massachusetts Boston, 100 Williams T. Morrissey Blvd., Boston, MA, 02125; Email: chi.wan@umb.edu; Tel: 617-287-7683. Yan Wang is from DeGroote School of Business at McMaster University, 1280 Main Street West, Hamilton, Ontario, L8S 4L8; Email: ywang@mcmaster.ca; Tel: 905-525-9140 ext. 23984; Phone: 617-287-7720. We thank Matthew Serfling and Anjan Thakor for helpful comments and suggestions. All errors and omissions are our own.

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Using the near universe of online job postings from 2007 to 2019, we construct a firm-level metric of local labor market concentration. We find that firms hiring in more concentrated labor markets tend to have higher financial leverage. The positive relation between labor market concentration and financial leverage is more pronounced when the firm hires low-skilled workers and workers from routine-intensive occupations. To establish causality, we exploit the establishment of Amazon HQ2 in Crystal City, Virginia as an exogenous shock to the local labor market concentration, and find results that are consistent with our baseline result.

Introduction

A large literature has studied the economic role played by the degree of concentration in the labor market. Theory suggests that a higher degree of labor market competition – loosely defined as employers competing for job candidates with similar skill sets – reduces the negotiating power of the firm over the employees. Intuitively, a competitive local labor market (i.e., a large number of employers trying to hire the same limited pool of workers in a geographic location) generates greater (less) bargaining power for the employees (employers) in the wage-setting as workers have more outside options and can play off one firm against another (Azar, Marinescu, Steinbaum, and Taska 2020; Benmelech, Bergman, and Kim 2020; Qiu and Sojourner 2019; Webber 2015; Rinz 2018). Conversely, in a more concentrated market, the balance of power shifts from employees to employers as firms have to fight less with each other to draw resources from a broader pool of workers, resulting in lower equilibrium wages.[1] For example, the bargaining power of high-tech firms like Apple or Microsoft will decrease if they are concerned that a tough stand in negotiation when hiring a talented computer engineer in a competitive labor market would push the talent to a competitor.

Higher bargaining power for the firm – i.e., a higher degree of labor market concentration – can arise from labor market frictions such as friction associated with job search, geographic mobility, non-compete or no-poaching agreements, as well as heterogeneous preferences over job characteristics. For example, employees cannot easily switch jobs as a reaction to wage reduction due to mobility restrictions (Sokolova and Sorensen 2018) or no-poaching agreements among major franchisors' contracts (Krueger and Ashenfelter 2018).[2] Labor market concentration exhibits substantial time-series changes (Benmelech et al. 2020, Autor, Dorn, Katz, Petterson, and Van Reenen 2020) as well as geographical variation: Rinz (2018) and Hershbein, Macaluso, and Yeh (2019) point out that, even though national labor market concentration

[1] See, for example, Azar et al. (2020), Benmelech et al. (2020), Qiu and Sojourner (2019), Webber (2015), Rinz (2018), Hershbein, Macaluso and Yeh (2019), Arnold (2020).
[2] Therefore, labor market is considered to be more prone to monopsony than the product market to monopoly (Manning 2003).

has increased over time, local labor market concentration has generally been decreasing by at least 25% since 1976.[3]

Labor market concentration, by changing the relative bargaining power of employers vs. workers in labor negotiations, will directly impact the major firm policies. Traditionally, the literature has extensively studied the impact of local labor market concentration on the relative bargaining power between employers and employees and its consequences on wages and labor supply. However, scarce attention has been paid to the impact of local labor market concentration on the firm's own financial policies. This is mainly due to the lack of a granular labor market database at the firm level that allows for computing a measure that captures a firm's exposure to local labor market concentration.

This paper attempts to fill this gap by studying how local labor market concentration shapes firms' financial policies using a novel dataset that tackles empirical difficulty. In theory, there are at least three different reasons why local labor market concentration can impact firms' capital structure. First, local labor market concentration, by increasing the bargaining power of the employers and depressing workers' wages, will increase profitability and strengthen the firm's incentives to borrow to get tax shields. Second, the lower bargaining power of employees in a concentrated labor market will disincentivize employees to demand a wage premium for bearing the financial distress risk, decreasing the indirect costs of financial distress and allowing the firm to increase financial leverage. Prior literature points out that because financial distress impairs job security, employees often require higher wages to compensate them for bearing the financial distress risk. This raises the overall cost of debt financing and leads firms to adopt a more conservative financial policy (Titman 1984; Berk, Stanton, and Zechner 2010).[4] Third, the higher

[3] It is likely to due to the large dispersion across industry-level concentration and a decreasing trend in the covariance between a local labor market's size and its concentration level over the past decades (Hershbein, Macaluso, and Yeh 2019).

[4] Prior literature finds that financially distressed firms not only significantly cut down workers but also struggle to retain their existing employees. For example, Benmelech, Bergman, and Seru (2011) and Benmelech, Frydman, and Papanikolaou (2018) find that financial constraints play an important role in shaping a firm's employment decision. Agrawal and Matsa (2013) show that bond defaults lead to a 27% decrease in firm employment in the two years following the defaults. Falato and Liang (2015) identify sharp employment cuts following loan covenant violations, especially among firms with larger financial frictions and weaker employee bargaining power. Graham et al. (2019) find that employees' earnings fall by 10% by the year their firms file for bankruptcy. Baghai et al. (2017) also show that employees with higher ability are more likely to leave a company approaching bankruptcy than an average

bargaining power of the firm relative to the employees in a concentrated labor market will increase the firm's "flexibility" to cut down wages and discharge workers, effectively lowering the proportion of fixed costs relative to variable costs (i.e., its operating leverage) and allowing the firm to increase financial leverage. Higher (lower) operating leverage raises (decreases) the costs associated with financial distress risk for a given level of debt (e.g., restructuring costs) and incentivizes the firms to decrease (increase) financial leverage (Mandelker and Rhee 1984; Mauer and Triantis 1994; Simintzi, Vig and Volpin 2015; Serfling 2016; Gustafson and Kotter 2017; Favilukis, Lin, and Zhao 2020).[5] Taken together, these considerations suggest that a concentrated local labor market increases employer power and allows firms to adopt a more aggressive financial policy.

While the theory is simple and provides relatively clear and unanimous predictions, empirical evidence on this topic is scarce. There are mainly two empirical challenges that have hindered progress in this direction. The first key hurdle is the availability of a proper proxy for the degree of a firm's exposure to labor market concentration that has sufficient time series and cross-sectional variation. We overcome this issue by exploiting a "big data" repository of U.S. employers' job postings compiled by Burning Glass Technologies (BGT).[6] These data cover the near-universe of online job postings in 2007, and continuously from 2010 through 2019. Importantly, this comprehensive data source contains detailed geographic information on the location of hire, the occupation of each vacancy (SOC), the job title, name of the employer, education, and knowledge requirement, which makes it possible to construct, for each firm-

employee. The theoretical paper by Jaggia and Thakor (1994) shows that firms use less financial leverage if they would like to induce more firm-specific human capital investments from employees. Assuming that it is much more costly to induce investments in firm-specific human capital in a competitive labor markets, firms will lower their financial leverage.

[5] For example, Simintzi, Vig, and Volpin (2015) and Serfling (2016) find that operating leverage crowds out financial leverage in the setting of employment protection law changes. Gustafson and Kotter (2017) find that firms respond to minimum wage increase by decreasing their financial leverage. Favilukis, Lin, and Zhao (2020) demonstrate that a negative economic shock raises a firm's operating leverage and its credit risk so that a firm tends to lower its financial leverage.

[6] BGT dataset has been used for several recent publications, including Deming and Kahn (2018), Hershbein and and Kahn (2018), Hershbein and Macaluso (2019), Schubert, Stansbury and Taska (2019), Azar et al. (2020), Deming and Noray (2020).

commuting zone (CZ)-skill (SOC) cluster, a measure of local labor market concentration as reflected in job postings.

Our empirical strategy is best illustrated using a simple example. Suppose Firm A hires both software engineers and data scientists in both San Francisco-San Mateo-Redwood (CZ 294), as well as the Cambridge-Newton-Framingham (CZ 76); Firm B hires in the same skill categories but in San Francisco-San Mateo-Redwood (CZ 294) and Minneapolis-St. Paul-Bloomington (CZ 47). That is, Firm A and Firm B share the same skill categories in which they hire workers, but differ in one of the geographic areas (Firm A and Firm B both hire in the Silicon Valley area, but Firm A hires from an arguably more competitive area (CZ 76) than Firm B (CZ 47). The firm-level labor market concentration then aggregates the hiring-weighted local labor market concentration measure (Herfindahl-Hirschman Index (HHI)) across the dimensions of commuting zone and skill cluster. In this case, Firm B, with higher exposure to local labor concentration than Firm A, is expected to have higher financial leverage.

This measure has several distinct advantages in capturing local labor market concentration over other prior measures constructed from U.S. Census data or CareerBuilder.com. Census data only provides data on employment at the Commuting Zone-industry or county-industry level (Benmelech et al. 2020; Lipsius 2018; Rinz 2018).[7] Such labor market competition measures computed at the location-industry level can be highly correlated with product market competition. BGT data, which provides detailed information on the employer, job title, occupation, and job location, allows us to construct a more refined local labor market concentration measure at the firm-CZ-SOC (i.e., the firm, commuting zone, and skill) level. The data from CareerBuilder.com has limited data coverage on occupation which restricts the analysis of the overall effect of local labor market concentration in the U.S. (Azar, Marinescu, and Steinbaum 2019, 2020).[8]

[7] For example, Rinz (2018) and Lipsius (2018) use the U.S. Census Bureau's Longitudinal Business Database (LBD) data to calculate labor market power by commuting zone and four-digit NAICS industry at the national and/or demographic group levels. Benmelech et al. (2020) use the plant-level LBD data to construct the Herfindahl-Hirschman Index of employment concentration at the U.S. county-industry (4-digit SIC) level.

[8] Azar, Marinescu, and Steinbaum (2019, 2020) use online job postings from CareerBuilder.com across 17 occupations to construct a local employer concentration measure by commuting zones and occupation.

The second empirical hurdle lies in the difficulty of isolating the effect of labor market competition from that of product market competition. Intuitively, product market competition and labor market competition can be closely related. For example, high-tech firms like Apple and Microsoft not only compete for specialized talents i.e. computer engineers but also compete for the similar products they offer i.e. cloud computing. The bargaining power of Apple for hiring talents in the local labor market depends on the labor demand from similar competitors. In the meanwhile, high-tech firms' ability to compete in the product market will also depend on their ability to attract specialized labor. This traditionally creates a very complex endogeneity issue. We overcome such issue and establish causality by exploiting the establishment of Amazon HQ2 in Crystal City, Arlington, Virginia.

The Amazon HQ2 serves as an ideal laboratory for our identification for three main reasons: First, the experiment has a clearly defined and well-publicized timeline, which allows us to focus on firms that were present even before the Amazon HQ2 announcement. Second, the job categories and the required skillsets associated with those jobs at Amazon HQ2 are well defined.[9] This unique feature allows us to pinpoint the treatment and control groups at the occupation level. Lastly, by focusing on a single location, our results would not be driven by time-varying location-specific variables (both the observed ones and the unobserved ones). Moreover, the Amazon HQ2 experiment allows us to distinguish the effect of the labor market competition independently of the product market competition given that the establishment of Amazon HQ2 only affects the labor market but not the product market. In other words, Amazon's entry affects the demand for skilled labor in the specific geographical area without affecting the degree to which Amazon is selling in the area and therefore not affecting product market competition.

We test our hypothesis using a sample of 19,491 firm-year observations over the period from 2007 to 2019. Our main finding is that firms with a higher degree of labor market concentration have higher

[9] These categories include software development, finance and global business services, project management (both technical and non-technical), systems, quality, and security engineering, sales, advertising, and account management, operations, IT, and support engineering, solutions architect, human resources, business and merchant development, business intelligence, public relations and communications, data science, audio/video/photography production, facilities, maintenance, and real estate, etc. The exact list is at: https://www.amazon.jobs/en/locations/arlington

financial leverage. In terms of economic effect, an increase in one standard deviation of local labor market concentration is correlated with a 1% (0.6%) increase in book leverage (market leverage), which implies a 3.5% (2.8%) increase relative to the sample mean. This relation is robust to using alternative measures of leverage (i.e., book leverage, market leverage, net book, and net market leverage) and different specifications (i.e., controlling for the firm, year, the local market, and industry x year fixed effects). Our finding is also robust to alternative measures of labor market concentration using different definitions of labor market location and occupation codes. This finding supports our working hypothesis that firms hiring in more concentrated local labor markets have a higher negotiating power relative to their employees, and adopt a more aggressive financial policy.

Furthermore, the impact of labor market concentration on firm leverage should be stronger for jobs that are more likely to substitute and thus with lower employees' negotiation power. Typical examples would be routine-intensive workers whose jobs can be automated by computerization (e.g., Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2006; Goos, Manning, and Salomons 2014; Autor and Dorn 2013) and low-skilled labor with limited eduction backgrounds (e.g., Rinz 2018; Azar, Marinescu and Steinbaum 2020; Qiu and Sojourner 2019; Hershbein, Macaluso and Yeh 2019; Benmelech et al. 2020; Azar et al. 2020). Consistent with our expectations, we find that the documented effect of local labor market concentration on financial leverage is stronger among these occupations.

As mentioned above, one concern in this type of analysis is that the positive relation between labor market concentration and firm leverage is endogeneity. Specifically, an unobservable omitted variable could affect both the labor market concentration and firm leverage, in which case our results so far could be reflecting a spurious correlation. To alleviate this concern and to establish causality, we exploit the establishment of Amazon HQ2 in Crystal City, Arlington, Virginia. Using a difference-in-differences (DID) empirical specification, we find that treated local firms, i.e., firms affected by Amazon's entry into the Crystal City region, reduce their leverage more than local firms that are unaffected (the control group). This finding echoes our baseline results that firms exposed to higher (lower) local labor market concentration adopt a more aggressive (conservative) financial policy.

The existing literature on labor and leverage has also studied the strategic role of debt (e.g., Bronars and Deere 1991; Perotti and Spier 1993; Dasgupta and Sengupta 1993; Matsa 2010). It has been argued that firms strategically choose their financial policies to attain a better bargaining position in future negotiations with employees – e.g., firms choose to increase financial leverage and lower their cash reserves to deter workers from extracting rents. If leverage is chosen to increase the bargaining power of the firm, a reducation in the bargaining power of the employees (e.g., higher labor market concentration) should allow the firm to lower its financial leverage. Our results point in a different direction documenting a positive relation between financial leverage and local labor market concentration. This is consistent with the intuition that, in the case of a change in labor market concentration, the change in bargaining power of the emplyees relative to the firm is related to an exogenous reason the firm can hardly bargain with. That is, an increase in leverage will hardly lower the bargaining power of the employees that can find alternative jobs. In fact, threatening employees with the cost of financial distress due to higher leverage will only scare them away or induce them to ask even higher salary to compensate for them.

Our paper mainly contributes to two strands of literature. By studying a firm's capital structure, we build on a voluminous body of work that intends to understand the determinants of capital structure. While early work tends to focus on straightforward firm attributes (e.g., Titman and Wessels 1988; Rajan and Zingales 1995; and Lemmon, Roberts, and Zender 2008), recently the literature has focused on frictions in the labor market such as workers' unemployment risk (e.g., Agrawal and Matsa 2013), employee firing costs (e.g., Serfling 2016; Simintzi, Vig, and Volpin 2015), or unionization (e.g., Schmalz 2016). Our paper focuses on whether the dynamic tradeoff that firms face concerning their employees in various local labor markets helps shape firms' financial policy. Our finding implies that labor market concentration, by shifting bargaining power from workers to employers, allows the firm to adopt a more aggressive financial policy, which could influence its ability to undertake future investment opportunities.

Our paper also relates to a large literature in labor economics that investigates labor market power. Prior studies document that increased employer power in the local labor market compresses workers' earnings (Azar et al. 2020; Benmelech et al. 2020; Qiu and Sojourner 2019; Webber 2015; Rinz 2018;

Hershbein, Macaluso and Yeh 2019; Arnold 2020), increases wage inequality (Webber 2015; Rinz 2018), and affects the demand for different labor skills (Hershbein, Macaluso and Yeh 2019; Deming and Kahn 2018; Hershbein and Kahn 2018; Deming and Noray 2020). Our paper adds to this literature by using the universe of online job postings to create a new local labor market concentration measure at different geography and location clusters and investigating the effect of local labor market concentration on a firm's financial policy.

The remainder of this paper is organized as follows. Section 2 details the construction of key variables and data sources. Section 3 discusses the empirical findings. Section 4 concludes.

2. Data and Variables

In this section, we describe our data sources, the construction of the sample, and key variable definitions in our empirical analysis.

2.1 Data

We obtain data from two primary sources. First, accounting and aggregate financial information of nonfinancial U.S. public firms are obtained from Compustat. We exclude observations for which total assets or total sales are missing. Second, we obtain information on online job postings from Burning Glass Technologies (BGT hereafter). BGT provides a "big data" repository that covers the near-universe of online job postings in 2007, and then continuously from 2010 to 2019. BGT uses artificial intelligence technologies to collect over 3 million online job postings daily from more than 50,000 job boards and corporate sites. Importantly, BGT ensures the integrity of job postings by removing duplicate ads and categorizing job descriptions using standardized occupation and skill families (O*NET job codes and Standard Occupational Classification (SOC) families).[10] In terms of occupation composition, as pointed out

[10] BGT only captures the new job posts in every period – i.e., job posts that last more than a period and are not filled will not reappear in next year in the BGT database. Also, BGT cleans the duplicated listings if it collects the same job posts from various platforms.

by prior studies (Hershbein and Kahn, 2018), BGT provides wide coverage of occupations: it includes a total of 836 6-digit SOC occupations, which is as comprehensive as those reported in Occupational Employment Statistics. This broad coverage of the occupation presents a substantial strength over databases using a single vacancy source such as CareerBuilder.com. Compared with the Job Openings and Labor Turnover Survey (JOLTS) which typically provides vacancies at an aggregated level and contains relatively little information about the characteristics of the job postings, the BGT database has the advantage of providing detailed information on each job posting: BGT contains unique identifiers for each job posting, the name of the employer posting the job, occupation, industry, geography (e.g., FIPS and corresponding MSA or commuting zones), as well as education, certification, and categories of skill requirements. The detailed geographic information and the skill categories allow for defining the local labor market at a highly granular level, e.g., commuting zone (CZ)-skill (SOC) level, and a large sample of firm-level analysis.

To construct our measure of local labor market concentration, we lastly conduct a two-step matching process between Compustat and BGT to construct our final sample. Given our focus on a firm-level analysis, we restrict our BGT sample to job postings with non-missing employer names that posted at least 3 job postings over the sample period.[11] We first use fuzzy name matching techniques to match both databases based on the employer names and Compustat firm names. This process involves the matches between multiple employer names stated in slightly different formats and one Compustat firm name. For example, employer names “Air products chemical inc”, “Air products & chemicals”, and “Air products chemicals” are all matched to “Air Products & Chemicals”. After the fuzzy matching, we manually clean the name-matching pairs to ensure the quality of these matches. Our final analytical sample consists of 19,491 firm-year observations, corresponding to 3,070 unique Compustat firms.

2.2 Local labor market concentration (LLMC)

[11] Employer name is missing in approximately 30-40% of job postings which is primarily from those listings that do not reveal employer names.

One key difference between our approach and earlier studies is the construction of an effective measure to capture employer power. Earlier studies on specialized labor markets focus on a direct approach – estimating the wage elasticity of the labor supply curve to individual firms (e.g., Manning 2011; Azar, Marinescu, and Steinbaum, 2020; Banfi and Villena-Roldán 2019). Recent studies measure employer power using a more comprehensive labor market concentration measure.[12] For example, Rinz (2018) and Lipsius (2018) use the Census LBD data to calculate labor market power by commuting zone and four-digit NAICS industry at the national and/or demographic group levels. Benmelech et al. (2020) use the plant-level U.S. Census Bureau's Longitudinal Business Database (LBD) data to construct the Herfindahl-Hirschman Index (HHI) of employment concentration at the U.S. county-industry (4-digit SIC) level.

However, Census data does not allow for constructing the labor market concentration at the occupational level. To compute an occupational-level labor market power, Qiu and Sojourner (2019) estimate the occupational distribution of employment within each industry year and impute employment by occupation to each establishment. Azar, Marinescu, and Steinbaum (2020) use online job postings from CareerBuilder.com across 17 occupations to construct a local employer concentration measure by commuting zones and occupation. Azar et al. (2020) construct a more comprehensive employer power measure at the occupation-commuting zone level using the online US job openings from Burning Glass Technologies (BGT), which allows for assessing the overall impact of employer power at a more refined occupation-local level.[13]

In this paper, we follow the construction of Azar et al. (2020) of the local labor market concentration. To construct a firm-level labor market concentration, we first utilize the detailed geographical and skill cluster information of job postings in BGT to construct a metric that measures the local labor market

[12] Azar, Marinescu, and Steinbaum (2019) show a negative correlation between labor market concentration and labor elasticity to the firm at the commuting zone-occupation (SOC 6-digit) market, which implies that both labor market concentration and labor supply elasticity measure employer power.

[13] The use of job vacancies, rather than employment, to compute the local labor market concentration can better capture the opportunities available to the workers at a given time period.

concentration for each pair of Commuting Zone (CZ)-SOC (6-digit) clusters.[14] This allows for a comprehensive and disaggregated measure of local labor market concentration at the occupational level across a large group of industries. As a robustness test, we also construct our measure using different definitions of occupations (e.g., 5-digit SOC code) and geographical locations (e.g., US counties or US states).

Specifically, to measure a firm i's exposure to local labor market concentration, for each local labor market m, defined at the commuting zone (CZ) × occupation (6-digit SOC) level, we first calculate the total number of job posts in the local labor market m in year t ($V_{m,t}$) and the total number of job posts of the firm i in year t ($V_{i,t}$) as follows:

$$V_{m,t} \equiv \sum_{i} V_{i,m,t} \tag{1a}$$

$$V_{i,t} \equiv \sum_{m} V_{i,m,t} \tag{1b}$$

where $V_{i,m,t}$ is the number of firm i's job posts in local labor market m in year t. Then we calculate the fraction of firm i's job posts in local labor market m in year t,

$$S_{i,m,t} = V_{i,m,t}/V_{m,t}. \tag{1c}$$

Next, we compute the local labor market concentration index in the local labor market m in year t using the Herfindahl-Hirschman Index, which takes the sum of squares of the factions of job posts across all the firms operating in the local market m in year t, as below,

$$HHI_{m,t} = \sum_{i \in m} S_{i,m,t}^2. \tag{2}$$

This measure follows the standard literature about local labor market concentration where a low (high) value of HHI suggests that firms operating in the local labor market m have limited (large) market power when recruiting employees from local market m.

[14] Commuting zones are geographic area definitions based on a group of counties and developed by the United States Department of Agriculture (USDA) in a way to better delineate local economies. The communting zones of our analysis is defined based on the USDA's 2000 Census communting zones, see https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/.

To measure a firm's overall exposure to local labor market concentration, we consider a weighted sum of local HHI in the form of $\sum_m \omega_{i,m,t} \times HHI_{m,t}$, where $\omega_{i,m,t}$ is defined as $\omega_{i,m,t} = V_{i,m,t}/V_{i,t}$. It captures the relative importance of market m to the firm's entire hiring effort. We then define our key variable as a proxy for the degree of Local Labor Market Concentration (LLMC) as:

$$LLMC_{i,t} = \sum_m \omega_{i,m,t} \times HHI_{m,t} = \sum_m \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}. \tag{3}$$

A higher level of LLMC indicates that firm i exposes to a more concentrated local labor market with many job candidates with similar skill sets in the same region competing for job openings by a limited number of employers.

For our baseline analysis, we calculate the labor market concentration at the commuting zone and 6-digit SOC level. We also consider three alternative measures using different definitions of occupation groups and geographical locations. $LLMC_{i,t}(By\ county)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. county × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ state)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. state × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ SOC\ 5\ digit)$ is a weighted sum of HHI calculated from local labor markets defined at the commuting zone (CZ) × occupation (5-digit SOC) level.

In Table 1, we report the mean, median, the 25th, the 75th percentiles, and standard deviation of the four local labor market concentration measures (LLMCs). In our baseline market definition as a SOC-6 occupation by commuting zone, the average value of the firm-level LLMC measure is 0.1158 with a standard deviation of 0.152. In terms of the hiring market, an average firm hires from 18 commuting zones and 468 local labor markets defined by commuting zone and 6-digit SOC occupation. This implies that on average firm exposes to a relatively competitive labor market.

2.3 Other firm-level variables

We construct four measures of financial leverage to capture firm-level capital structure decisions, including book leverage, market leverage, net book leverage, and net market leverage. Book leverage is calculated as the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by the book value of assets (*ta*). Market leverage is calculated as the book value of long-term debt (*dltt*) plus debt in current liabilities (*dlc*) divided by market value of debt and equity (long-term debt (*dltt*) plus debt in current liabilities (*dlc*) plus market value of equity (*prcc_f*×*csho*)). While market leverage is more closely related to the theoretical prediction of the optimal debt level, a large portion of the variation in market leverage is driven by the variation of the market value of equity rather than changes in debt values (Welch 2004). Alternatively, two net leverage ratios are also considered. The net book leverage is defined as net debt (i.e., total debt minus cash and other marketable securities) over total assets while the net market leverage is defined as net debt (i.e., total debt minus cash and other marketable securities) over the market value of assets.

We include a set of firm-level control variables that relate to the firm's capital structure decisions (e.g., Rajan and Zingales 1995; Serfling 2016; Simintzi et al. 2015). Firm size (*Size*) is defined as the logarithm of a firm's total assets, which controls for diversification and the risk of default. The market-to-book ratio (*M*/*B*) is computed as the ratio of the market value of equity plus the book value of debt over the book value of debt plus equity, which works as an indicator of growth opportunities. The return on assets (*ROA*) is the ratio of EBIT over total assets, which measures a firm's profitability and works as a proxy for the level of a firm's internal funds. The dividend payment (*Dividend*) is an indicator of whether the firm paid a common dividend, which proxies for financial constraints. Tangibility (*Tangibility*) is calculated as net property, plant, and equipment scaled by total assets, which control for the effect of pledgeable collateral assets on a firm's borrowing capacity. A modified Altman *z*-score (MacKie-Mason 1990) captures a firm's financial strength and bankruptcy likelihood. The extended labor share (*ELS*) is computed as the imputed labor expenses divided by the value-added of a firm as in Donangelo et al. (2019) (i.e., the imputed labor expenses are calculated as an industry average labor costs per employee, i.e., total staff expense divided by the operating income before depreciation plus the change in inventory, multiplied by the number of employees in a firm), which captures the labor intensity of a firm's operation.

We report the mean, median, the 25th, the 75th percentiles, and standard deviation of the dependent variables and independent variables in Table 2. The distribution of leverage ratio in our study is comparable to those reported in prior literature (e.g., Serfling 2016). The average book (market) leverage is about 28.58% (22.315%). An average firm holds 1272.2 million total assets and has a market-to-book ratio of 2.5. On average, there is 41.23% of firm-year observations where dividends are paid. The average ROA and tangibility of a firm are -0.013 and 0.512 respectively in our sample. On average, a firm has a modified Atlamn *z*-score of -0.682 and an extended labor share of 0.555.

2.4 Univariate results

In Table 3, we sort the sample firms into five quintiles every year based on our baseline local labor market concentration measure and report the average of book leverage, market leverage, net book leverage and net market leverage by quintiles. The table shows that all four measures of financial leverage increase monotonically with the firm's exposure to local labor market concentration. For instance, average book leverage (market leverage) increases from 23.44% (15.81%) in the bottom-HHI quintile to 33.21% (29.05%) in the top-HHI quintile. The difference in average book leverage (market leverage) between the top- and bottom-HHI quintiles is 9.77% (13.24%) and is highly significant. The univariate analysis provides the first preliminary evidence of a positive relation between a firm's exposure to local labor market concentration and financial leverage ratios.

3. Empirical Results

In this section, we discuss our main empirical findings. Section 3.1 provides the baseline results on the correlation between local labor market concentration and financial leverage. Section 3.2 provides a discussion on the robustness of the documented relation between local labor market concentration and financial leverage. In Section 3.3, we examine how the impact of labor market concentration on firm leverage varies with employees' bargaining power to shed more light on the main findings.

3.1 Baseline results

We start by assessing the overall effect of local labor market concentration on a firm's financial policy. We estimate the following firm-level fixed effects regression model:

$$Leverage_{i,t} = \beta LLMC_{i,t-1} + \gamma' X_{i,t-1} + \alpha_i + \tau_t + \varepsilon_{i,t}, \tag{4}$$

where *i* and *t* denote firm and year, respectively. The dependent variable, $Leverage_{i,t}$, is firm i's leverage ratio in year t. We use four different proxies to measure firm leverage: book leverage, market leverage, net book leverage, and net market leverage. $LLMC_{i,t-1}$ is the firm-level labor market concentration measure in Equation (3). The main coefficient of interest is β, which measures the correlation between a firm's exposure to labor market concentration and firm leverage. We include firm fixed effect (α_i) to control for any time-invariant, unobservable firm-level characteristics that are relevant to a firm's capital structure, a year fixed effect (τ_t) to account for time-varying macroeconomic conditions.

Table 4 Panel A reports the baseline results on the relation between local labor market concentration and financial leverage. Our results show consistent positive coefficients on $LLMC_{i,t-1}$ across all four different measures of financial leverage. For example, coefficients associated with $LLMC_{i,t-1}$ range from 0.0407 to 0.0718, and all are statistically significant. In terms of economic effect, an increase in one standard deviation of local labor market concentration is correlated with a 0.9% (0.6%) increase in book leverage (market leverage), which implies a 3.1% (2.5%) increase relative to the sample mean. The economic significance is even more prominent for net book and net market leverage: an increase in one standard deviation of local labor market concentration is correlated with a 1.3% (1%) increase in net book leverage (market leverage). These findings are consistent with our hypothesis that a concentrated labor market shifts the bargaining power from workers to employers, which leads firms to adopt a more aggressive capital structure.

As an alternative specification, a local market fixed effect (φ_m) is added to the baseline specification in equation (4). Certain unobserved local economic characteristics or industry structures may be correlated with both the concentration of the local labor market and the firm's use of debts. For example, many more high-tech firms compete for computer engineers in San Francisco-San Mateo-Redwood (CZ 294) than in Minneapolis-St. Paul-Bloomington (CZ 47) and such high-tech firms tend to have low financial leverage. Table 4 Panel B reports the baseline results by controlling for the local market fixed effects. The local market is defined as the commuting zone (CZ) of the firm's headquarters which is assumed to be the major market where the firm hires.[15] We observe that the coefficients associated with $LLMC_{i,t-1}$ show a higher magnitude and remain statistically significant across all four measures of financial leverage.

Furthermore, some unobserved industry-level time-varying characteristics may be correlated with both a firm's capital structure decisions and a firm's exposure to local labor market conditions. Previous studies (e.g., MacKay and Phillips 2005) find that different industries exhibit notable differences in their capital structure. For example, changes in product market competition can be related to a firm's use of financial leverage and a firm's demand for skill-specific talents. To address these concerns, we further include both a local labor market fixed effect and an industry×year fixed effect in Equation (4) to account for any time-varying industry dynamics. We report these results in Panel C of Table 4. In this more stringent specification, our documented positive relation between local labor market concentration and a firm's leverage ratio remains statistically significant and economically strong.

Table 5 presents additional findings using alternative measures of a firm's exposure to local labor market concentration. $LLMC_{i,t}(By\ county)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. county × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ state)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. state × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ SOC\ 5\ digit)$ is a weighted sum of HHI calculated from local labor markets defined at the commuting zone (CZ) × occupation (5-digit SOC) level. We follow the same specification as Panel C of Table 4 and find that the documented positive relation between a firm's exposure to local labor market concentration and financial leverage remains intact using different definitions of hiring markets.

[15] About 80% of the firms in the sample have the commuting zone of headquarter as their largest hiring market.

3.2 Robustness Checks

In this section, we provide additional robustness checks to address several concerns about our baseline analysis. One concern about our main measure is that the time-varying weight assigned to different hiring markets may be endogenous. For example, firms that enter into financial distress may choose to hire less from a competitive labor market and more from a concentrated labor market where they have more market power. In other words, firms with higher financial leverage may be associated with higher exposure to local labor market concentration and vice versa. To address the concern that the time-varying market weights assigned to different hiring markets may correlate with both $LLMC_{i,t-1}$ and the firm's financial leverage, we consider an unweighted local HHI where the degree of local labor market concentration is proxied by the simple average of the local HHI across all the firm's hiring labor markets, as follows:

$$LLMC_{i,t}(Unweighted) = \frac{1}{N}\sum_m HHI_{m,t}. \quad (5)$$

If the positive relation we documented between $LLMC_{i,t-1}$ and financial leverage is driven by the mechanical relation between a firm's choice of hiring markets (not HHI) and its financial condition, then we should not observe any significant relation between the unweighted $LLMC_{i,t-1}(Unweighted)$ and leverage ratios. We report our results on the relation between the unweighted $LLMC_{i,t-1}(Unweighted)$ and financial leverage in Panel A of Table 6. The results show that the coefficient associated with the equally weighted $LLMC_{i,t-1}(Unweighted)$ are consistently positive and statistically significant, which implies that our baseline results are not driven by the correlation between the weights assigned to hiring markets and the firm's financial condition.

Another concern of our baseline analysis is that the time-varying economic shocks to different hiring markets may correlate with the changes in labor market concentration and the firm's financial policy. For example, a positive and persistent economic shock to a hiring market can encourage incumbent firms to hire more workers and incentivize new firms to enter the local labor market, both of which decrease the local labor market concentration. At the same time, the incumbent firms enjoy a higher cash balance and lower financial leverage due to the rising demands and higher profits during the economic upswings. To fully control for such an effect, we will need to include all of the hiring markets x time fixed effects, which is not possible to be saturated with the current regression model. Note that an average firm hires from 18 commuting zones and 468 local labor markets defined by commuting zone and 6-digit SOC occupation. To partially alleviate such a concern, we implement the following tests. Given that 45% of the firms only hire from one commuting zone and 80% of the firms' largest hiring market is the commuting zone of its headquarters, we control for the time-varying economic conditions of the firm headquarters' commuting zones by including a Commuting Zone (CZ) x year fixed effect. The results are presented in Table 6 Panel B. The positive and significant coefficients for $LLMC_{i,t-1}$ remains intact, suggesting that at least the time-varying economic shock to the firm's largest hiring market is not the reason for the positive relationship between local labor market concentration and leverage ratios. We further address the endogeneity issue in Section 4.

Lastly, one may be concerned that firms' capital structure preceding the recent financial crisis might be jointly related to various firm decisions and labor market outcomes (Giroud and Mueller 2017). Our results in Table 4 use the entire BGT coverage, which includes a gap between 2007 and 2010. In Panel C of Table 6, we re-estimate our baseline specifications (i.e., equation (4)) by excluding the year 2007. Overall, our results remain unchanged if we exclude the year 2007.

3.3 Cross-sectional analysis

To further substantiate our hypothesis, we now explore how the relationship between local labor market concentration and financial leverage varies with the employee's bargaining power. Schubert et al. (2020) show a large heterogeneity in labor market concentration across occupations and regions, and workers in different occupations and regions have access to substantially different outside options e.g., bargaining power.

To investigate whether the positive impact of local labor market concentration on financial leverage is related to the changes in the relative bargaining power of employees vs employers, we test the cross-sectional within-market variation of the positive relation across a few occupation characteristics that are indicative of different employee bargaining power.

The relative bargaining power of workers depends on the extent to which they can complete tasks that others cannot (Matsa 2018). A vast literature on skill-biased technological change highlights that automation and computerization replaced routine-intensive or low-skilled jobs and shifted labor demand toward the non-routine or high-skilled labor in recent decades – i.e., the workers that possess the mathematical or cognitive skills that cannot be automated by computerization (e.g., Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2006; Goos, Manning, and Salomons 2014; Autor and Dorn 2013). In other words, within each local labor market, workers in routine-intensive occupations or low-skilled workers suffer from a greater disadvantage in relative bargaining power in negotiating wages and employment with employers than those in non-routine occupations or high-skilled labor due to their high substitutability by automation technologies. Following these arguments, if an increase in local labor market concentration increases employer power and limits workers' bargaining position which allows firms to use higher financial leverage, then we should expect that such an impact is stronger for firms that hire routine or low-skilled labor with high substitutability and low bargaining power.

We classify the occupations into routine and non-routine occupations following Autor and Dorn (2013). We merge job task requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT) to their corresponding SOC occupation classification to quantify routine, abstract, and manual task content by occupation. We first calculate a summary measure of routine task intensity for each occupation as in Autor and Dorn (pp.1570, 2013),

$$RTI_i = \ln\left(Task_i^R\right) - \ln\left(Task_i^M\right) - \ln\,(Task_i^A), \tag{6}$$

where $Task_i^R$, $Task_i^M$, and $Task_i^A$ are the routine, manual, and abstract task inputs for occupation i. This measure increases with the importance of routine tasks in each occupation and decreases in the importance of manual and abstract tasks. Then we classify occupations with RTI_i above the 66th percentile of RTI_i as routine-intensive occupations and the rest occupations as non-routine-intensive occupations.

We split $LLMC_{i,t}$ based on whether or not an occupation is considered as a routine-intensive occupatioin, and the routine component of $LLMC_{i,t}$ is defined as follows. The non-routine component ($SOC \notin Routine$) is defined in parallel.

$$LLMC_{i,t}^{Routine} = \sum_{m:\text{SOC}\in\text{Routine}} \omega_{i,m,t} \times HHI_{m,t} = \sum_{m:\text{SOC}\in\text{Routine}} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}. \tag{7a}$$

$LLMC_{i,t}^{Routine}$ is the weighted sum of local labor HHI across all local labor markets (m defined at the SOC-CZ level) where the SOC is a routine-intensive occupation.

In a similar vein, we also classify high-skilled and low-skilled hires using the education requirements in the BGT job postings. We define low-skilled workers as those with the education requirement of high school diplomat or lower and low-skilled workers as those with education requirement of college and above. Then we split $LLMC_{i,t}$ based on the fraction of job posts that require low-skilled vs. high-skilled workers, and the low-skilled component of $LLMC_{i,t}$ is defined as follows. The high-skilled component ($V_{imt} \notin Low\ Skilled$) is defined in parallel.

$$LLMC_{i,t}^{lowskilled} = \sum_{V_{imt}\in\text{LowSkilled}} \omega_{i,m,t} \times HHI_{m,t} = \sum_{\text{V}_{\text{imt}}\in\text{LowSkilled}} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}. \tag{7b}$$

$LLMC_{i,t}^{Lowskilled}$ is the weighted sum of local labor HHI across all job posts considered low-skilled worker hires. We then repeat our regression analysis in equation (4) using the decomposed $LLMC_{i,t}$ measure based on routine and non-routine occupation classification or low-skilled and high-skilled hires.

The results are reported in Table 7. Panel A reports the results of the sample split based on routine vs. non-routine intensive occupations. Panel A shows that the coefficients for $LLMC_{i,t}^{Routine}$ are positive and statistically significant regardless of the leverage ratio considered; while the coefficients for $LLMC_{i,t}^{nonRoutine}$ are all insignificant. For instance, for the specifications using the book leverage (market leverage) as the dependent variable, the coefficient for $LLMC_{i,t}^{Routine}$ is 0.056 (0.041) with a *t*-statistic of 2.63 (1.93). By contrast, the coefficients for $LLMC_{i,t}^{nonRoutine}$ are only –0.0164 (–0.0174) with *t*-statistics of –0.016 (–0.017), respectively. Our finding implies that the effect of local labor market concentration on financial leverage is more evident among the routine-intensive occupations that have a relatively weak bargaining position in negotiating wages and employment.

Panel B reports the results of the sample split based on the low-skilled and high-skilled hires. Again we see that the coefficients for the low-skilled component of LLMC are positive across four measures of financial leverage and statistically significant at 5% in three out of four leverage ratios. We do not observe any significant relation between the high-skilled component of LLMC and financial leverage. Our results indicate that the capital structure decisions of firms tend to be more responsive to the changes in labor market concentration in the segment of low-skilled hires. The findings in Table 7 combined further substantiate our hypothesis that the positive impact of local labor market concentration on financial leverage is related to the changes in the relative bargaining power of employees vs employers.

4. The Experiment: Amazon's HQ2 establishment

In this section, we use the establishment of Amazon's second headquarter (HQ2) in Crystal City as a quasi-natural experiment to local (incumbent) firms' local market concentration and provide further analysis to address the remaining endogeneity concerns.

4.1 Amazon HQ2: the empirical setting

So far, our documented positive relationship between local labor market concentration and firms' financial leverage is only a correlation and may be endogenous. In particular, an unobservable omitted variable could affect both the local labor market concentration and a firm's use of financial leverage. For instance, recent studies (e.g., Giroud and Rauh, 2019) find that state taxation has a direct impact on the reallocation of business activities. Thus, lower state-level personal income tax rates could lead to firms allocating business activities away from other states with higher personal tax rates, resulting in lower local market concentration. Simultaneously, low personal tax rates can also directly influence a firm's leverage ratio (Graham 1999). In this case, state taxation is the omitted variable that affects both labor market concentration and financial leverage, rendering our baseline effect the result of a spurious correlation.

Although the extensive range of fixed effects included in our empirical specification already accounts for many different factors (see our discussion in Section 3.2), such as the local labor market fixed effect to control for any location-specific variation, the industry-times-year fixed effect to control for any time-variant industry shocks, and the local labor market-times-year fixed effect to control for any time-variant economic shocks, the aforementioned possibility could still exist. To further mitigate this concern and establish causality, we exploit a unique empirical setting in which there is an exogenous shock to firms' local labor market concentration.

Specifically, we exploit the establishment of Amazon's second headquarter (HQ2) in Crystal City, Arlington, Virginia, as a quasi-natural experiment. The Amazon HQ2 is a well-publicized event with clearly defined timelines, making it an ideal experiment. The main intuition is that Amazon's entry into the Crystal City area significantly changes the local labor market concentration for those incumbent firms that hire from the same occupation categories as Amazon (the treated firms), but not for others without much overlap (the control firms).

The Amazon HQ2 plan was announced in September 2017, to expand its existing headquarters in Seattle, Washington. Amazon intended to spend $5 billion on construction and employ as many as 50,000 workers upon completion of its HQ2. After receiving proposals from over 200 cities in Canada, Mexico, and the United States that offered a combination of tax breaks, expedited construction approvals, etc., the company announced a shortlist of 20 finalists on January 19, 2018, after which the candidate localities continued to detail or expand their incentive packages. On November 13, 2018, New York City and Northern Virginia were announced to be the winners of the HQ2 sites, but the announcement of the HQ2 campus in New York City immediately drew withering criticism and pushback. Subsequently, on February 14, 2019, Amazon announced that it would cancel the planned New York City location due to opposition,[16] which leaves Northern Virginia the one and only Amazon HQ2 location. As part of the agreement, Virginia offered performance-based incentives which included a workforce cash grant of $550 million for the first

[16] For the specific issues associated with New York's opposition to Amazon HQ2, please see, e.g., https://www.wsj.com/articles/amazon-cancels-hq2-plans-in-new-york-city-11550163050.

25,000 jobs Amazon created that paid an average salary of $150,000 by 2030. The aggressive hiring by Amazon's HQ2 thus introduced an exogenous shock to LLMC faced by incumbent local firms that would have to compete with Amazon for certain workers.[17] We employ Amazon HQ2 expansion as our primary empirical setting to establish causality.

There are several reasons why the Amazon HQ2 expansion serves as an ideal laboratory. First, the skill categories which Amazon hires and the required skill sets of these jobs are well defined. This allows us to first calculate, for each skill category, the change in local labor market concentration before and after Amazon's construction of HQ2. As a result, it allows us to clearly define the treatment and control groups: incumbent firms that experience a significant decrease in the local market concentration after Amazon's entry compared to before are defined as the treated group, while others that experience almost no change brought by Amazon's entry are defined as the control group.

Second, the shock associated with Amazon's HQ2 to the local labor market is largely unanticipated by local incumbent firms. It is difficult for the incumbent local firms to foresee Amazon's entry into Crystal City, as there was no clear frontrunner in the race before the final announcement. In fact, 9 days before announcing final picks, Amazon was still in negotiations with Dallas and other cities on its planned second headquarters.[18] Due to the unanticipated nature of the shock, it is extremely unlikely that any effect we documented is driven by local incumbent firms adjusting their financial leverage by anticipating any direct effects or externalities associated with the entry of Amazon.

Third, any positive externalities brought about by Amazon's entry, if any, would only bias us against finding a *negative* impact on the treated firm's financial leverage brought by Amazon's entry. For example, one such positive externality is that Amazon's entry into Crystal City attracts people to move into the region,

[17] These categories include software development, finance and global business services, project management (both technical and non-technical), systems, quality, and security engineering, sales, advertising, and account management, operations, IT, and support engineering, solutions architect, human resources, business and merchant development, business intelligence, public relations and communications, data science, audio/video/photography production, facilities, maintenance, and real estate, etc. The exact list is at: https://www.amazon.jobs/en/locations/arlington

[18] See https://www.wsj.com/articles/amazon-in-late-stage-talks-with-cities-including-crystal-city-va-dallas-new-york-city-for-hq2-1541359441.

leading to an appreciation of local residential and commercial real estate values. To the extent that firms usually use real estate as collateral against which they borrow, such appreciation in collateral value has been found to increase the firm's leverage ratio (e.g., Titman and Wessels 1988; Cvijanović 2014; Rampini and Viswanathan 2013). Such a collateral effect would bias against us in finding that the lower local market concentration (or intensified local labor market competition) brought about by Amazon's entry significantly reduces treated firms' leverage ratio relative to the control sample.

Fourth, and potentially more important, Amazon's entry impacts the labor market but does not affect the product market competition given the internet-sale model of Amazon. This allows us to concentrate on the effect of the labor market without concerning any confounding effect from the product market.

Lastly, one concern about our experiment using Amazon HQ2 establishment is that even though the establishment of Amazon HQ2 was announced in 2018 but the construction only took place until 2020 and is expected to be completed in 2023. To validate that Amazon indeed starts hiring right away after the announcement in Crystal City but not waits until the construction is fully finished, we check the number of job postings by Amazon in the Crystal City Area. We find that in 2019, one year after the announcement alone, there are about 3,849 job posts by Amazon in commuting zone 74 (crystal city area) using the BGT dataset, in which about 1,372 or one-third of the job postings are in the occupation family "Information technology". This effectively proves that the announcement of Amazon HQ2 establishment has an immediate effect on the local labor market dynamics.

4.2 Amazon HQ2: A difference-in-difference (DiD) analysis

To operationalize our tests, we first identify the SOCs (Standard Occupational Classification) from job advertisements posted by Amazon HQ2. Next, we trace back to 2015, two years before Amazon HQ2 was made public, and identify the set of firms in Northern Virginia that had an overlap with Amazon's job postings in their SOCs that is greater than or equal to 30%.[19]

[19] Our results are robust to using alternative thresholds.

Given that these firms have a similar demand for skills in their labor force, they face a significant decrease in their local labor market concentration after Amazon enters the region. The intuition is that for these skill categories, the local labor market concentration has significantly decreased with Amazon's entry into the locality, shifting the bargaining power from employers to workers. Correspondingly, we define these affected incumbent firms as our treated sample, with the remaining firms in the Northern Virginia region constituting our control sample. It is worth noting that by taking full advantage of the granularity in the BGT data, our way of defining the treated group and the control group transcends the industry boundary because two firms in the same industry can hire in significantly different skill categories.

Moreover, the fact that we are able to focus on a single location controls for time-varying location-specific variables (both the observed ones and the unobserved ones), as these local shocks would influence both the control group and the treated group at the same time. Indeed, the main difference between the treated and the control variables, as previously pointed out, lies in their differential overlap with Amazon's demand for specific skills.

To get a sense of the specific skill categories in which Amazon HQ2 hires the most workers, we extract Amazon's hiring patterns from 2015 to 2017 in its Seattle HQ location which corresponds to CZ 171. As is shown in Panel A of Table 8, the top five SOCs in which Amazon's Seattle HQ hires are Software Developers, Marketing Managers, General Managers, Computer Occupations, and Operational Managers, of which Software Developers (SOC 15-1132) constitute almost 22% of all Amazon's job vacancies.

Because Amazon HQ2 serves a similar function as Amazon's HQ in Seattle, we assume that Amazon HQ2's hiring in CZ 74 will be in the similar skill categories as CZ 171. Accordingly, for each incumbent firm i in CZ 74, we identify the set of skill categories in which the firm posted job advertisements between 2015 and 2017. A firm is coded as treated if it hires in the same SOC categories in which Amazon HQ posted (between 2015 and 2017) 30% or more of its jobs. The remaining firms form the control group, which includes firms with a limited or no overlapping labor demand with Amazon in CZ 74 as well as firms that do not hire in CZ 74. Defining the overlap in job categories before the actual event of Amazon HQ2 establishment ensures that our results are not driven by the possible shift in firms' hiring behavior after Amazon enters the Crystal City area.

We employ a DiD empirical methodology to estimate how the treated group and the control group differentially adjust their capital structure before and after the establishment of HQ2. Specifically, we estimate the following regression:

$$Leverage_{i,t} = \beta Treated_i \times Post_t + \gamma' X_{i,t-1} + \alpha_i + \tau_t + \varphi_m + \varepsilon_{i,t}, \quad (8a)$$

where *i* and *t* index firm and year, respectively. $Treated_i$ is an indicator variable that is set equal to one if a firm's hiring needs have sufficient overlap with Amazon HQ2 as defined previously. $Post$ is an indicator variable that is set equal to one in 2019 and zero for the pre-treatment period from 2015 to 2017. The parameter of interest is β, which measures the differential change in leverage before and after the shock between the treated group and the control group. Similar to Equation (4), we also include firm fixed effects, year fixed effects, and firm headquarter commuting zone fixed effects in the specification. Because of this, the main terms $Treated_i$ and $Post_t$ are subsumed by the fixed effects. We also exclude the announcement year of 2018 to avoid any confounding effect during the event year.

We report our DiD results in Panel B of Table 8. In columns (1) to (4), across all four proxies of the leverage ratio, we find a negative and statistically significant coefficient on $Treated_i \times Post_t$. For example, in column (1), the coefficient of -0.021 implies that compared to the control group, the treated group reduced their leverage ratio by 2.1% after the shock, which is economically sizeable. This effect is statistically robust across all the different specifications. These findings indicate that treated firms opt for a more conservative financial policy relative to the control firms in the period following the entry of Amazon HQ2 expansion into Crystal City.

In columns (5)-(8), we augment our model with industry×year fixed effects to further control for the effect of time-varying industry dynamics. Again, the coefficients associated with the interaction term ($Treated_i \times Post_t$) remain negative and statistically significant across all columns. This implies that our findings are not driven by any industry shocks that may correlate with both the firm's use of financial leverage and the firm's exposure to local labor market concentration changes caused by Amazon HQ2 entry.

4.3 Amazon HQ2: additional findings

Alternative control groups

In the previous analysis, we used a control group made of firms that are located in CZ 74 without significant overlap with Amazon's skill demand, as well as all other firms in our sample that are not located in the CZ 74 locality. One potential concern is that firms that are located outside of CZ 74 may not serve as good controls if the firm location is endogenous. This concern is already alleviated by the headquarter's commuting zone fixed effects. To further address this concern, we re-estimate our DiD regression by limiting the control sample to only the firms located in CZ 74 and adjacent CZs that have an overlap in skill demands with Amazon. This results in a much smaller sample of only 251 observations.

We re-estimate Equation (5) on this subsample and report our results in panel A of Table 9. We find that our results remain statistically significant, and their economic magnitude becomes much larger. Note that the various fixed effects along with the control variables are quite demanding of the underlying sample of 251 observations. Taken together, these DiD results provide further support to the fact that the documented positive relation between local labor market concentration and firm leverage is likely causal.

Parallel trend assumption

For any DiD estimation, the parallel trend assumption needs to hold to ensure its validity. In our context, this means that absent the Amazon HQ2 shock, the leverage ratio of the treated group and the control group would have followed a similar trend before the actual treatment. To test this, we replace the dummy variable $Post_t$ with three dummies: *AmazonHQ2 year(-2)*, *AmazonHQ2 year(-1)*, and *AmazonHQ2 year(+1)*, where *AmazonHQ2 year(-2)* (i.e., 2016) and *AmazonHQ2 year(-1)* (i.e., 2017) are dummy variables that equal one for two years and one year before the Amazon HQ2 announcement, respectively. Finally, *AmazonHQ2 year(+1)* is a dummy that equals one for the year after the Amazon HQ2 shock (i.e., 2019). If local firms that share similar skill demands with Amazon were changing their leverage ratio prior to the actual shock because they anticipate any externalities associated with Amazon's entry, then we should see an ''effect'' of the shock already before their actual occurrence. In particular, if the *AmazonHQ2 year(-1)* or *AmazonHQ2 year(-2)* is significant, then this would be symptomatic of reverse causality. We evaluate the parallel trend assumption by estimating the following regression:

$$\begin{aligned} Leverage_{i,t} &= \theta_1[Treated_i \times AmazonHQ2\ year(-2)] \\ &+ \theta_2[Treated_i \times AmazonHQ2\ year(-1)] \\ &+ \theta_3[Treated_i \times AmazonHQ2\ year(+1)] + \gamma' X_{i,t-1} + \alpha_i + \tau_t + \varphi_m + \varepsilon_{i,t}, \end{aligned} \tag{8b}$$

where all the variables are defined analogously as in Equation (5a) except for the dummy variables. We repeat the above specification in columns (1)-(4) in the full sample of treated and control firms and columns (5)-(8) in the sample of treated and control firms located in CZ 74. As is shown in Panel B of Table 9, the coefficient on $Treated_i \times AmazonHQ2\ year(-2)$ and $Treated_i \times AmazonHQ2\ year(-1)$ are both small and statistically insignificant, while the coefficient on *AmazonHQ2 year(+1)* is negative and significant in most of the specifications. This is true for both the larger sample that includes firms located outside of CZ 74 as control firms and the smaller sample that only retains the firms in the CZ 74 region that do not meet the skill overlapping requirement. Overall, there appears to be no differential trend between the control group and the treated group prior to the actual Amazon shock, which is consistent with a causal interpretation.

To visualize the parallel trend, we also graph the estimated coefficients on the aforementioned interaction terms as well as their corresponding confidence intervals for both the more inclusive sample as well as the more restrictive subsample in panels A and B of Figure 1, respectively. Both figures show that the parallel trend holds well in our experiment, assuring the empirical setting and our causal interpretation.

Placebo tests

Finally, we address the concern that because our DiD analysis defines treatment and control groups across different SOC categories – i.e., treated firms focus on hiring in certain SOC categories like computer occupations or software developers while control firms mainly hire other SOC categories such as service or manufacturing – some unobserved time-varying firm-specific or occupation-specific factors can have differential impacts on the labor market concentration in the overlapping skills and non-overlapping skills categories. However, if this were the case, it would result in subsequent changes in the financial leverage of firms hiring workers for both overlapping and non-overlapping SOCs simultaneously. For example, the mounting privacy lawsuits against high-tech firms over the years impose significant legal and reputational costs on the affected firms, which can lead them to adopt a more conservative leverage policy for reasons not related to the Amazon shock.[20] To address this concern, we conduct a placebo test using firms located in the commuting zones of other 18 shortlisted cities and have the overlapping SOC categories as Amazon.[21]

We use the firms located in other 18 shortlisted cities during the same period of the Amazon HQ2 construction for our placebo test. The firms in the placebo test are subject to similar unobserved time-varying SOC-specific trends (e.g., privacy lawsuits) but do not experience a significant change in labor market concentration in the same sample period. If our findings were driven by the unobserved factors mentioned above, we should expect similar findings among the firms in the sample of the placebo test.

We repeat our DiD analysis but use the firms located in the other 18 shortlisted cities during the same period of the Amazon HQ2 construction. Specifically, we define our placebo "treated" firms as those firms with overlapping SOCs located in the 18 shortlisted cities two years before the entry of Amazon to Crystal City (e.g., who presumably share some common SOC characteristics and are subject to similar time-varying SOC-specific trends) and placebo "control" firms as those firms with limited or no overlapping SOCs located in the same region and repeat the difference-in-difference analysis as in equation (8a) using the placebo "treated" and "control" firms.

We report our results in Panel C of Table 9. Overall, we do not observe any significant decline in firm leverage between the treated firms with overlapped SOCs and the control firms located in other 18 shortlisted cities during the same period of the Amazon HQ2 shock. Taken together, these results imply that our finding is not driven by any unobserved firm-specific or occupation-specific trends between the

[20] See https://www.wsj.com/articles/privacy-problems-mount-for-tech-giants-11548070201.
[21] Toronto is excluded.

high-tech firms hiring mainly technology people and firms hiring from different talent pools but rather by the changes in local labor market concentration brought about by Amazon's HQ2 entry.

Conclusion

In this paper, we analyze the impact of labor market concentration on firms' capital structure decisions. Using the near universe of online job postings between 2007 and 2019, we find a robust and significant positive association between labor market concentration and leverage ratios. We also explore the cross-sectional variation in our documented effect by focusing on various factors that influence the balance in negotiating power between employers and employees. Specifically, we find that the documented positive impact of labor market concentration on firm leverage is most pronounced for workers from routine-intensive occupations and low-skilled workers.

To establish causality, we exploit the unique setting of the period when Amazon HQ2 is established in Crystal City, Arlington, Virginia. By taking advantage of the granularity in the job posting data from BGT, we use hiring information at Amazon HQ in Seattle to classify incumbent firms in the Crystal City based on their overlap with Amazon's job advertisements before Amazon HQ2's actual entry, allowing for a clean empirical setting that abstracts away from time-varying location-specific confounding factors. Using a difference-in-differences specification, we find that treated firms reduce their leverage significantly more compared to the control group, suggesting that the positive relationship between labor market concentration and firm leverage is likely causal.

Our paper's finding provides some of the first large-sample evidence that dynamics in arguably the most important input markets, i.e., labor markets have a significant causal impact on firms' financing decisions. Firms' capital structure decisions seem to account for the relative power of the firm in its hiring in the various local labor markets. Understanding the dynamic nature of financial policy adjustment in response to labor market conditions is a fruitful area for future research.

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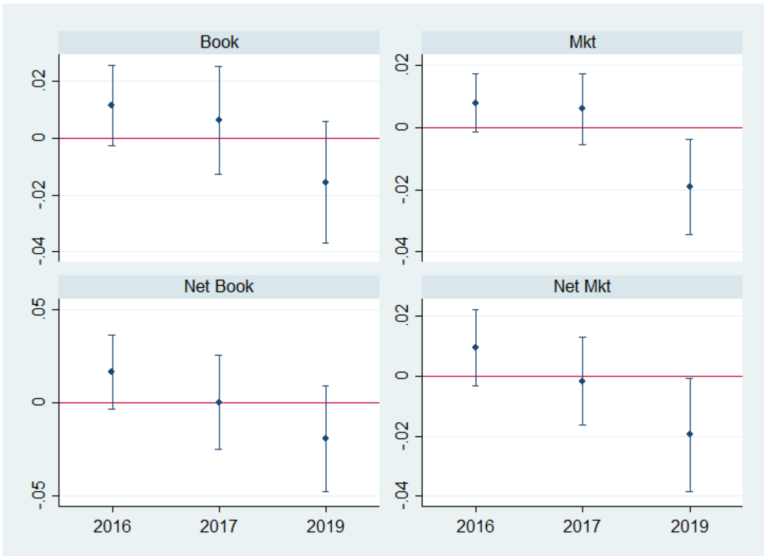
Figure 1. Amazon's HQ2 Difference-in-Difference Analysis: Parallel Trend
This figure displays estimated coefficients of the tests on the treated firms' adjustment on their leverage ratios in response to Amazon's entry relative to the control firms. Specifically, it displays the time series of coefficient estimates of the interaction term between the treated variable and three event period indicators (i.e., two years before and one year after the entry), including their 90% confidence interval for the difference-in-different regressions reported in Table 9, Panel B. Panel A displays the coefficient estimates using the full sample of treated and control firms as reported in columns (1)-(4) in Table 9, Panel B. Panel B displays the coefficient estimates using only the sample of treated and control firms located in CZ 74 or adjacent CZs as reported in columns (5)-(8) in Table 9, Panel B.

Panel A: Full Sample



Panel B: Treated and Controls Firms in CZ 74 or Adjacent CZs

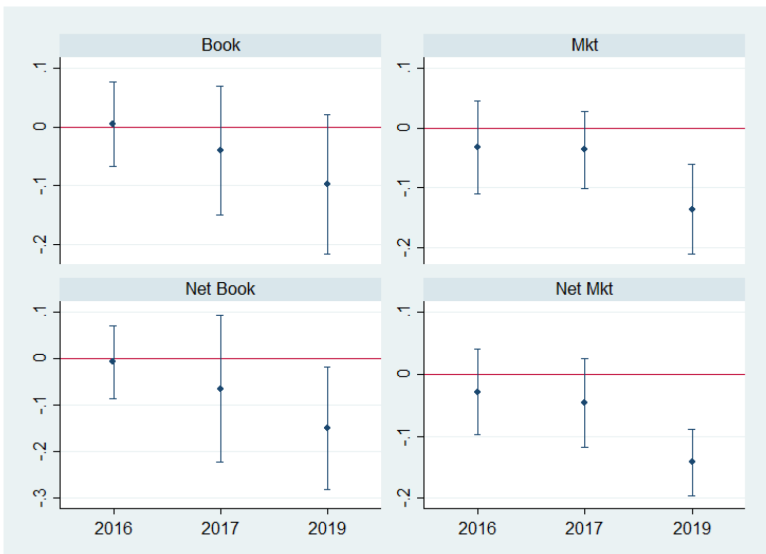


Table 1. Summary Statistics: Firm's exposure to local labor market concentration

This table presents the descriptive statistics of measures of the firm's exposure to local labor market concentration under various market definitions using the job posting data from Burning Glass Technology (BGT). $LLMC_{i,t}$ is the weighted sum of the local HHI across all the firm's hiring labor markets where local labor markets are defined at the U.S. commuting zone (CZ) × occupation (6-digit SOC) level. Three alternative measures are aggregated using different definitions of occupation and/or geographic locations. $LLMC_{i,t}(By\ county)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. county × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ state)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. state × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ SOC\ 5\ digit)$ is a weighted sum of HHI calculated from local labor markets defined at the commuting zone (CZ) × occupation (5-digit SOC) level.

	N	Mean	STD	25th	Median	75th
LLMC	19491	0.1158	0.1520	0.0277	0.0626	0.1414
LLMC (By County)	19243	0.1785	0.1946	0.0460	0.1094	0.2408
LLMC (By State)	19476	0.0498	0.0640	0.0155	0.0313	0.0598
LLMC (By SOC 5-digit)	19491	0.0914	0.1323	0.0213	0.0470	0.1039

Table 2. Summary statistics: Dependent and control variables

This table presents the descriptive statistics of the dependent and control variables. Book leverage (Book) and market leverage (Market) is computed as the ratio of long-term debt plus current liability over total assets and the ratio of long-term debt plus debt in current liability over the market value of assets (i.e., the book value of debt plus the market value of equity) respectively. Net book leverage (Net book) and net market leverage (Net market) are defined as net debt (i.e., total debt minus cash and other marketable securities) over total assets and net debt over the market value of assets, respectively.

The control variables are defined as follows: firm size (Size) is defined as the logarithm of firms' total asset; the market-to-book ratio (M/B) is computed as the ratio of the market value of equity plus book value of debt over the book value of debt plus equity; the return on assets (ROA) is computed as the ratio of EBIT over total assets; Tangibility is calculated as net property, plant, and equipment scaled by total assets; dividend payment (Dividend) is an indicator for whether the firm paid a common dividend in a firm-year; A modified Altman *z*-Score (AZ) (MacKie-Mason 1990) is computed as the sum of 1.2*working capital/total asset, 1.4*retained earnings/total assets, 3.3*EBIT/total assets and sales/total assets; Extended labor share (ELS) is computed as the imputed labor expenses divided by the value-added of a firm as in Donangelo et al. (2019) (i.e., an industry average labor costs per employee, i.e., total staff expense divided by the operating income before depreciation plus the change in inventory, multiplied by the number of employees in a firm), which captures the labor intensity of a firm's operation.

Panel A: Summary statistics for financial leverage ratios

	N	Mean	STD	25th	Median	75th
Book	19491	0.2858	0.4710	0.0668	0.2359	0.3889
Mkt	19491	0.2231	0.2267	0.0313	0.1598	0.3419
Net Book	19491	0.0656	0.5529	-0.1933	0.0929	0.3037
Net Mkt	19491	0.0807	0.3217	-0.0850	0.0611	0.2625

Panel B: Summary Statistics for control variables

	N	Mean	STD	25th	Median	75th
Log(at)	19491	7.1485	2.1790	5.6646	7.1503	8.6475
M/B	19491	2.4962	5.2082	1.2122	1.6665	2.6611
ROA	19491	-0.0126	0.4921	-0.0068	0.0599	0.1083
Tangibility	19491	0.5121	0.4630	0.1661	0.3594	0.7631
dividend	19491	0.4123	0.4923	0.0000	0.0000	1.0000
AZ	19491	-0.6824	23.1888	0.2919	1.2342	2.1523
ELS	19491	0.5546	1.2949	0.3457	0.6065	0.8156

Table 3. Univariate Results

This table presents univariate findings of the relationship between leverage ratios and a firm's exposure to local labor market concentration. The sample firms are sorted into five quintiles each year based on the firm's exposure to local labor market concentration as defined in Section 2.2. $LLMC_{i,t}$ is the weighted sum of the local HHI across all the firm's hiring labor markets where local labor markets are defined at the U.S. commuting zone (CZ) × occupation (6-digit SOC) level. We report the average book leverage, market leverage, net book leverage and net market leverage in each quintile. Top – Bottom reports the differences in average financial ratios between the top and bottom quintiles of local labor market concentration.

	N	Book	Mkt	Net Book	Net Mkt
LLMC (Q1 - Bottom)	3903	0.2344	0.1581	-0.0942	-0.0377
(mean = 0.0151)					
LLMC (Q2)	3899	0.2601	0.1816	-0.0324	0.0095
(mean = 0.0349)					
LLMC (Q3)	3898	0.2915	0.2207	0.0744	0.0835
(mean = 0.0653)					
LLMC (Q4)	3899	0.3108	0.2649	0.1698	0.1575
(mean = 0.1231)					
LLMC (Q5 - Top)	3892	0.3321	0.2905	0.2109	0.1909
(mean = 0.3413)					
Top – Bottom		0.0977^{***}	0.1324^{***}	0.3051^{***}	0.2286^{***}
p-value		[<0.01]	[<0.01]	[<0.01]	[<0.01]

Table 4. Baseline Results

This table presents regression results of leverage ratios on a firm's exposure to local labor market concentration and relevant control variables. All specifications include the control variables as follows: firm size, book-to-market ratio, ROA, tangibility, dividend, modified Altman *z*-score, and extended labor share. Specifications in Panel A include firm and year fixed effect. Specifications in Panel B include firm, year and local market fixed effects. The specifications in Panel C include the firm, year, local market, and industry × year fixed effects. $LLMC_{i,t}$ is the weighted sum of the local HHI across all the firm's hiring labor markets where local labor markets are defined at the U.S. commuting zone (CZ) × occupation (6-digit SOC) level. All other variables are as defined in Table 2. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Baseline results with firm and year fixed effects

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$	0.0585***	0.0370**	0.0848***	0.0662***
	(2.89)	(2.06)	(3.59)	(2.97)
$Log(Assets)_{t-1}$	0.0282**	0.0491***	0.0716***	0.0435***
	(2.55)	(9.39)	(6.03)	(5.25)
M/B $ratio_{t-1}$	-0.0090***	-0.0045***	-0.0114***	-0.0012
	(-2.62)	(-3.72)	(-3.07)	(-1.05)
ROA_{t-1}	-0.0954	-0.0224**	-0.1069	-0.0178
	(-0.78)	(-2.40)	(-0.89)	(-1.05)
$Tangibility_{t-1}$	0.1279**	0.1000***	0.1749***	0.1046***
	(2.42)	(7.82)	(3.20)	(5.68)
$Dividend_{t-1}$	0.0096	-0.0080	0.0172	0.0072
	(1.05)	(-1.16)	(1.64)	(0.77)
AZ_{t-1}	0.0001	-0.0005*	-0.0004	-0.0001
	(0.05)	(-1.74)	(-0.13)	(-0.17)
ELS_{t-1}	-0.0019	0.0011	-0.0032*	0.0003
	(-1.26)	(1.31)	(-1.72)	(0.17)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	19491	19491	19491	19491
Adj. R2	0.843	0.810	0.858	0.785

Panel B: Baseline results with firm, year and CZ fixed effects

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$	0.0652***	0.0407*	0.0959***	0.0718***
	(2.63)	(1.93)	(3.32)	(2.74)
$Log(Assets)_{t-1}$	0.0314***	0.0479***	0.0748***	0.0411***
	(2.83)	(8.58)	(6.11)	(4.46)
M/B $ratio_{t-1}$	-0.0090**	-0.0043***	-0.0114***	-0.0012
	(-2.51)	(-3.52)	(-2.95)	(-0.99)
ROA_{t-1}	-0.1023	-0.0197**	-0.1127	-0.0140
	(-0.74)	(-1.99)	(-0.83)	(-0.73)
$Tangibility_{t-1}$	0.1589***	0.1003***	0.2072***	0.1048***
	(2.89)	(7.43)	(3.69)	(5.25)
$Dividend_{t-1}$	0.0161	-0.0052	0.0246**	0.0113
	(1.55)	(-0.71)	(2.05)	(1.09)
AZ_{t-1}	0.0004	-0.0005	-0.0001	-0.0002
	(0.12)	(-1.61)	(-0.04)	(-0.21)
ELS_{t-1}	-0.0017	0.0010	-0.0034*	0.0001
	(-1.07)	(1.15)	(-1.72)	(0.05)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
N	16838	16838	16838	16838
Adj. R2	0.833	0.807	0.850	0.786

Panel C: Baseline results with firm, year, CZ, and industry x year fixed effects

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$	0.0573**	0.0422*	0.0809***	0.0596**
	(2.22)	(1.90)	(2.69)	(2.19)
$Log(Assets)_{t-1}$	0.0238**	0.0472***	0.0661***	0.0371***
	(2.09)	(8.75)	(5.18)	(3.98)
M/B $ratio_{t-1}$	-0.0097***	-0.0042***	-0.0123***	-0.0011
	(-2.68)	(-4.16)	(-3.22)	(-0.84)
ROA_{t-1}	-0.1137	-0.0179*	-0.1288	-0.0194
	(-0.75)	(-1.91)	(-0.87)	(-0.94)
$Tangibility_{t-1}$	0.1757***	0.0875***	0.2297***	0.1090***
	(2.89)	(6.19)	(3.72)	(5.15)
$Dividend_{t-1}$	0.0084	-0.0101	0.0176	0.0058
	(0.81)	(-1.47)	(1.46)	(0.55)
AZ_{t-1}	0.0006	-0.0005*	0.0002	0.0000
	(0.18)	(-1.89)	(0.05)	(0.04)
ELS_{t-1}	-0.0020	0.0009	-0.0036*	-0.0002
	(-1.23)	(1.05)	(-1.79)	(-0.16)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
N	16838	16838	16838	16838
Adj. R2	0.840	0.832	0.856	0.802

Table 5. Baseline Results: Alternative measures

This table presents regression results of leverage ratios on various alternative measures of a firm's exposure to local labor market concentration and relevant control variables. The specification follows Table 4, panel C. All specifications include the control variables as follows: firm size, book-to-market ratio, ROA, tangibility, dividend, modified Altman *z*-score, and extended labor share. The specifications include the firm, year, local market, and industry × year fixed effects. $LLMC_{i,t}(By\ county)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. county × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ state)$ is a weighted sum of HHI calculated from local labor markets defined at the U.S. state × occupation (6-digit SOC) level. $LLMC_{i,t}(By\ SOC\ 5\ digit)$ is a weighted sum of HHI calculated from local labor markets defined at the commuting zone (CZ) × occupation (5-digit SOC) level. All other variables are as defined in Table 2. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: LLMC (county)

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$(By county)	0.0501**	0.0521***	0.0731***	0.0638***
	(2.48)	(2.86)	(3.10)	(2.71)
Log(Assets)$_{t-1}$	0.0243**	0.0474***	0.0661***	0.0376***
	(2.09)	(8.68)	(5.10)	(3.99)
M/B ratio$_{t-1}$	-0.0097***	-0.0041***	-0.0124***	-0.0011
	(-2.67)	(-4.13)	(-3.22)	(-0.85)
ROA$_{t-1}$	-0.1142	-0.0174*	-0.1300	-0.0202
	(-0.75)	(-1.86)	(-0.87)	(-0.98)
Tangibility$_{t-1}$	0.1727***	0.0872***	0.2252***	0.1065***
	(2.85)	(6.25)	(3.68)	(5.28)
Dividend$_{t-1}$	0.0089	-0.0104	0.0184	0.0060
	(0.85)	(-1.51)	(1.53)	(0.56)
AZ$_{t-1}$	0.0007	-0.0005*	0.0002	0.0001
	(0.19)	(-1.89)	(0.06)	(0.08)
ELS$_{t-1}$	-0.0022	0.0009	-0.0039*	-0.0003
	(-1.32)	(1.04)	(-1.90)	(-0.21)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
N	16613	16613	16613	16613
Adj. R2	0.841	0.833	0.857	0.803

Panel B: LLMC (state)

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$(By state)	0.1257***	0.0668*	0.1839***	0.1186**
	(2.98)	(1.73)	(3.74)	(2.41)
$Log(Assets)_{t-1}$	0.0235**	0.0469***	0.0653***	0.0365***
	(2.05)	(8.69)	(5.09)	(3.92)
M/B $ratio_{t-1}$	-0.0097***	-0.0042***	-0.0124***	-0.0011
	(-2.68)	(-4.18)	(-3.23)	(-0.87)
ROA_{t-1}	-0.1137	-0.0179*	-0.1295	-0.0200
	(-0.75)	(-1.91)	(-0.87)	(-0.97)
$Tangibility_{t-1}$	0.1766***	0.0881***	0.2305***	0.1094***
	(2.90)	(6.23)	(3.73)	(5.17)
$Dividend_{t-1}$	0.0082	-0.0103	0.0172	0.0056
	(0.79)	(-1.49)	(1.43)	(0.52)
AZ_{t-1}	0.0006	-0.0005*	0.0002	0.0000
	(0.18)	(-1.90)	(0.05)	(0.05)
ELS_{t-1}	-0.0020	0.0010	-0.0037*	-0.0002
	(-1.23)	(1.12)	(-1.80)	(-0.10)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
N	16824	16824	16824	16824
Adj. R2	0.840	0.832	0.856	0.802

Panel C: LLMC (SOC 5-digit)

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$(By SOC 5-digit)	0.0740***	0.0504*	0.1048***	0.0804**
	(2.60)	(1.72)	(3.14)	(2.32)
$Log(Assets)_{t-1}$	0.0238**	0.0471***	0.0660***	0.0370***
	(2.08)	(8.74)	(5.17)	(3.98)
M/B $ratio_{t-1}$	-0.0097***	-0.0042***	-0.0123***	-0.0011
	(-2.68)	(-4.16)	(-3.21)	(-0.83)
ROA_{t-1}	-0.1136	-0.0178*	-0.1287	-0.0193
	(-0.75)	(-1.91)	(-0.87)	(-0.94)
$Tangibility_{t-1}$	0.1759***	0.0876***	0.2300***	0.1092***
	(2.89)	(6.21)	(3.73)	(5.16)
$Dividend_{t-1}$	0.0086	-0.0100	0.0179	0.0061
	(0.83)	(-1.46)	(1.49)	(0.57)
AZ_{t-1}	0.0006	-0.0005*	0.0002	0.0000
	(0.18)	(-1.89)	(0.05)	(0.04)
ELS_{t-1}	-0.0020	0.0009	-0.0037*	-0.0003
	(-1.23)	(1.04)	(-1.80)	(-0.17)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
N	16838	16838	16838	16838
Adj. R2	0.840	0.833	0.856	0.802

Table 6. Baseline Results: Robustness

This table presents regression results of several different robust tests on the relation between a firm's exposure to local labor market concentration and financial leverage. The specification of Panels A and C follow Table 4, panel C. The specification of Panel B includes firm, year, CZ x year, and industry x year fixed effects. All specifications include the control variables as follows: firm size, book-to-market ratio, ROA, tangibility, dividend, modified Altman z-score, and extended labor share. $LLMC_{i,t}$ is the weighted sum of the local HHI across all the firm's hiring labor markets where local labor markets are defined at the U.S. commuting zone (CZ) × occupation (6-digit SOC) level. $LLMC_{i,t}(Unweighted)$ is the simple average of the local HHI across all the firm's hiring labor markets. All other variables are as defined in Table 2. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: LLMC (Unweighted)

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$(Unweighted)	0.0515**	0.0446**	0.0744**	0.0605**
	(2.09)	(2.09)	(2.56)	(2.30)
$Log(Assets)_{t-1}$	0.0237**	0.0471***	0.0659***	0.0370***
	(2.07)	(8.74)	(5.16)	(3.98)
M/B $ratio_{t-1}$	-0.0097***	-0.0042***	-0.0123***	-0.0011
	(-2.68)	(-4.16)	(-3.22)	(-0.84)
ROA_{t-1}	-0.1137	-0.0179*	-0.1287	-0.0194
	(-0.75)	(-1.91)	(-0.87)	(-0.94)
$Tangibility_{t-1}$	0.1757***	0.0874***	0.2298***	0.1090***
	(2.89)	(6.19)	(3.72)	(5.15)
$Dividend_{t-1}$	0.0084	-0.0102	0.0176	0.0058
	(0.81)	(-1.48)	(1.46)	(0.55)
AZ_{t-1}	0.0006	-0.0005*	0.0002	0.0000
	(0.18)	(-1.89)	(0.05)	(0.04)
ELS_{t-1}	-0.0020	0.0009	-0.0036*	-0.0002
	(-1.23)	(1.04)	(-1.79)	(-0.16)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
N	16838	16838	16838	16838
Adj. R2	0.840	0.833	0.856	0.802

Panel B: Control for time-varying market effects – CZ of headquarters

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$	0.0624**	0.0416*	0.0863***	0.0546*
	(2.37)	(1.70)	(2.73)	(1.67)
$Log(Assets)_{t-1}$	0.0205*	0.0457***	0.0634***	0.0404***
	(1.69)	(8.41)	(4.69)	(4.28)
M/B $ratio_{t-1}$	-0.0099**	-0.0038***	-0.0125***	-0.0007
	(-2.43)	(-4.01)	(-2.95)	(-0.49)
ROA_{t-1}	-0.1245	-0.0160	-0.1394	-0.0184
	(-0.75)	(-1.62)	(-0.86)	(-0.83)
$Tangibility_{t-1}$	0.2025***	0.0900***	0.2574***	0.1180***
	(2.96)	(6.49)	(3.71)	(5.60)
$Dividend_{t-1}$	0.0052	-0.0094	0.0145	0.0075
	(0.48)	(-1.21)	(1.11)	(0.62)
AZ_{t-1}	0.0009	-0.0005*	0.0004	0.0001
	(0.25)	(-1.69)	(0.12)	(0.13)
ELS_{t-1}	-0.0022	0.0009	-0.0041*	-0.0002
	(-1.28)	(1.02)	(-1.90)	(-0.11)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ ×Year FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
N	16838	16838	16838	16838
Adj. R2	0.852	0.859	0.868	0.828

Panel C: Excluding year 2007

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC_{t-1}$	0.0569**	0.0426*	0.0804***	0.0599**
	(2.20)	(1.94)	(2.65)	(2.22)
$Log(Assets)_{t-1}$	0.0281***	0.0441***	0.0694***	0.0370***
	(2.80)	(8.09)	(5.88)	(3.82)
M/B $ratio_{t-1}$	-0.0105***	-0.0041***	-0.0130***	-0.0006
	(-2.58)	(-4.11)	(-3.07)	(-0.50)
ROA_{t-1}	-0.1470	-0.0193*	-0.1639	-0.0183
	(-0.89)	(-1.89)	(-1.01)	(-0.86)
$Tangibility_{t-1}$	0.1956***	0.0873***	0.2482***	0.1061***
	(3.26)	(6.02)	(4.07)	(4.71)
$Dividend_{t-1}$	0.0093	-0.0124*	0.0179	0.0014
	(0.86)	(-1.78)	(1.46)	(0.13)
AZ_{t-1}	0.0012	-0.0005*	0.0008	0.0002
	(0.36)	(-1.70)	(0.25)	(0.22)
ELS_{t-1}	-0.0017	0.0010	-0.0033	-0.0003
	(-0.99)	(1.17)	(-1.56)	(-0.21)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
N	16108	16108	16108	16108
Adj. R2	0.842	0.835	0.858	0.806

Table 7. Heterogeneity

This table evaluates the differential effect of a firm's exposure to the local labor market concentration. A firm's overall exposure to local labor market concentration ($LLMC_{i,t}$) is split based on whether an occupation is considered a routine-intensive or non-routine-intensive occupation (panel A), and whether hiring is on low-skilled or high-skilled workers (panel B). $LLMC_{i,t}^{Routine}$ ($LLMC_{i,t}^{NonRoutine}$) is the weighted sum of local labor HHI across all local labor markets (m defined at the SOC-CZ level) where the SOC is a routine-intensive (non-routine-intensive) occupation. $LLMC_{i,t}^{Lowskilled}$ ($LLMC_{i,t}^{Highskilled}$) is the weighted sum of local labor HHI across all job posts considered high-skilled worker hires.

The specification follows Table 4 Panel C and all specifications include the control variables as follows: firm size, book-to-market ratio, ROA, tangibility, dividend, modified Altman *z*-score, and extended labor share. The specifications include the firm, year, local market, and industry × year fixed effects. All other variables are as defined in Table 2. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Routine-intensive occupations vs. non-Routine intensive occupations

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC\_Routine_{t-1}$	0.0557***	0.0411*	0.0892***	0.0547**
	(2.63)	(1.93)	(3.37)	(2.00)
$LLMC\_NonRoutine_{t-1}$	-0.0164	-0.0174	0.0221	0.0501
	(-0.35)	(-0.64)	(0.44)	(1.36)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
Observations	16838	16838	16838	16838
R^2	0.840	0.832	0.856	0.802

Panel B: Low-skilled workers vs. high-skilled workers

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
$LLMC\_LowSkilled_{t-1}$	0.0449	0.0793**	0.0715**	0.0924***
	(1.57)	(2.56)	(2.11)	(2.81)
$LLMC\_HighSkilled_{t-1}$	0.0320	0.0035	0.0425	0.0267
	(0.88)	(0.14)	(1.03)	(0.82)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y
Observations	16838	16838	16838	16838
R^2	0.840	0.832	0.856	0.802

Table 8. Amazon's HQ2 Difference-in-Difference Analysis: Baseline Results

This table reports the regression results of the difference-in-difference analysis based on the establishment of Amazon's second headquarter (HQ2) in Crystal City, Arlington, Virginia. Panel A presents the skill categories of Amazon's HQ hiring during 2015-2017. Panel B reports the estimates of the difference-in-difference regressions as in equation (5a). $Treated_i$ is an indicator variable that is set equal to one if a firm's hiring needs overlap with Amazon HQ2 and zero otherwise. $Post$ is an indicator variable that is set equal to one in 2019 and zero for the pre-treatment period from 2015 to 2017. All specifications include the control variables as follows: firm size, book-to-market ratio, ROA, tangibility, dividend, modified Altman z-score, and extended labor share. The specification in columns (1)-(4) includes the firm, year, and local market fixed effects. The specifications in columns (5)-(8) include the firm, year, local market, and industry × year fixed effects. All control variables are as defined in Table 2. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Skill Categories of Amazon's HQ Hiring During 2015-2017

SOC	Description	Percentage
15-1132	Software Developers, Applications	0.219
11-2021	Marketing Managers	0.090
11-9199	Managers, All Other	0.085
15-1199	Computer Occupations, All Other	0.076
11-1021	General and Operations Managers	0.034

Panel B: Difference-in-Difference Analysis

	Book	Mkt	Net Book	Net Mkt	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	-0.021**	-0.026***	-0.024**	-0.023***	-0.022**	-0.024***	-0.025**	-0.022**
	(-2.23)	(-3.57)	(-2.13)	(-2.93)	(-2.17)	(-3.09)	(-1.98)	(-2.55)
Log(Assets)$_{t-1}$	0.028**	0.029***	0.050***	0.027***	0.029**	0.034***	0.051***	0.031***
	(2.37)	(4.16)	(3.60)	(3.20)	(2.55)	(5.15)	(3.54)	(3.62)
M/B ratio$_{t-1}$	-0.012**	-0.014***	-0.012*	-0.009***	-0.011**	-0.013***	-0.012*	-0.009***
	(-2.27)	(-6.63)	(-1.77)	(-3.80)	(-2.12)	(-6.64)	(-1.69)	(-3.61)
ROA$_{t-1}$	-0.040***	-0.023***	-0.045**	-0.017*	-0.039***	-0.026***	-0.046**	-0.021**
	(-2.65)	(-3.08)	(-2.49)	(-1.95)	(-2.63)	(-3.89)	(-2.55)	(-2.40)
Tangibility$_{t-1}$	0.080	0.037	0.185***	0.063	0.083	0.033	0.195***	0.064
	(1.27)	(0.97)	(2.72)	(1.36)	(1.32)	(0.87)	(2.73)	(1.34)
Dividend$_{t-1}$	0.006	0.011	0.014	0.012	-0.005	0.004	0.003	0.005
	(0.55)	(1.12)	(0.86)	(0.98)	(-0.40)	(0.42)	(0.19)	(0.42)
AZ$_{t-1}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.92)	(-13.92)	(-3.63)	(-9.40)	(-3.78)	(-13.87)	(-3.50)	(-8.76)
ELS$_{t-1}$	0.001	0.001	0.001	0.001**	0.001	0.001*	0.001	0.001**
	(1.42)	(1.46)	(1.01)	(2.56)	(1.33)	(1.67)	(1.03)	(2.39)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC2×Year FE					Y	Y	Y	Y
N	6102	6102	6102	6102	6102	6102	6102	6102
Adj. R2	0.100	0.156	0.106	0.119	0.172	0.283	0.155	0.206

Table 9. Amazon's HQ2 Difference-in-Difference Analysis: Further Tests

This table reports the estimates of the additional tests based on the difference-in-difference analysis. Panel A reports the estimates of the difference-in-difference analysis based on the treated and control firms located in CZ 74 and adjacent CZs. Panel B reports the time-series estimates of a granular difference-in-difference specification as in equation (8b). Panel C reports the estimates of the difference-in-difference analysis where placebo "treated" firms as those firms with overlapping SOCs located in the 18 shortlisted cities two years before the entry of Amazon to Crystal City (e.g., who presumably share some common SOC characteristics and are subject to similar time-varying SOC-specific trends) and placebo "control" firms as those firms with limited or no overlapping SOCs located in the same region. All specifications include the control variables as follows: firm size, book-to-market ratio, ROA, tangibility, dividend, modified Altman *z*-score, and extended labor share. The specifications in columns (1)-(4) of Panel A and C include the firm, year, and local market fixed effects. The specifications in Panel B and columns (5)-(8) of Panel A and C include the firm, year, local market, and industry × year fixed effects. All control variables are as defined in Table 2. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Limit the control firms to those located in CZ 74 and adjacent CZs

	Book	Mkt	Net Book	Net Mkt	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	-0.061**	-0.069***	-0.085**	-0.055*	-0.085*	-0.112***	-0.123***	-0.116***
	(-2.15)	(-2.66)	(-2.30)	(-1.96)	(-1.95)	(-2.79)	(-2.98)	(-3.84)
Log(Assets)$_{t-1}$	-0.008	0.033	0.034	0.019	-0.030	0.014	0.027	0.017
	(-0.46)	(1.47)	(1.19)	(0.82)	(-0.97)	(0.53)	(0.59)	(0.70)
M/B ratio$_{t-1}$	0.007	-0.008	0.022	0.013	-0.006	-0.027***	0.008	-0.002
	(0.96)	(-1.32)	(1.62)	(1.62)	(-0.40)	(-3.00)	(0.30)	(-0.23)
ROA$_{t-1}$	0.360***	0.175***	0.431***	0.192*	0.311*	0.083	0.530**	0.193*
	(3.75)	(2.68)	(2.65)	(1.85)	(1.88)	(0.95)	(2.03)	(1.71)
Tangibility$_{t-1}$	-0.299***	-0.014	-0.298**	-0.025	-0.169	0.080	-0.235	0.091
	(-3.10)	(-0.09)	(-2.10)	(-0.14)	(-1.05)	(0.41)	(-1.01)	(0.48)
Dividend$_{t-1}$	-0.068	-0.046*	-0.074	-0.040	-0.048	-0.049	-0.047	-0.058**
	(-1.53)	(-1.98)	(-1.42)	(-1.54)	(-0.64)	(-1.66)	(-0.53)	(-2.18)
AZ$_{t-1}$	-0.014***	-0.009***	-0.022***	-0.019***	-0.013**	-0.008**	-0.030***	-0.023***
	(-3.61)	(-2.76)	(-3.83)	(-3.13)	(-2.42)	(-2.24)	(-3.03)	(-5.04)
ELS$_{t-1}$	-0.012	-0.004	-0.011	-0.005	-0.021	-0.004	-0.034	-0.008
	(-0.99)	(-0.43)	(-0.60)	(-0.45)	(-1.10)	(-0.28)	(-1.40)	(-0.58)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC2×Year FE					Y	Y	Y	Y
N	251	251	251	251	251	251	251	251
Adj. R2	0.291	0.295	0.265	0.267	0.430	0.468	0.375	0.488

Panel B: Evaluation of the Parallel Trend Assumption

	Book	Mkt	Net Book	Net Mkt	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × AmazonHQ2 (-2)	0.011	0.008	0.017	0.009	0.005	-0.032	-0.007	-0.028
	(1.32)	(1.39)	(1.38)	(1.21)	(0.10)	(-0.70)	(-0.15)	(-0.69)
Treated × AmazonHQ2 (-1)	0.006	0.006	0.000	-0.002	-0.040	-0.036	-0.065	-0.046
	(0.54)	(0.85)	(0.03)	(-0.19)	(-0.61)	(-0.94)	(-0.69)	(-1.06)
Treated × AmazonHQ2 (+1)	-0.016	-0.019**	-0.019	-0.019*	-0.098	-0.136***	-0.149*	-0.142***
	(-1.19)	(-2.03)	(-1.11)	(-1.71)	(-1.38)	(-3.00)	(-1.90)	(-4.46)
Log(Assets)$_{t-1}$	0.029**	0.034***	0.051***	0.031***	-0.027	0.017	0.031	0.020
	(2.55)	(5.15)	(3.53)	(3.62)	(-0.86)	(0.60)	(0.66)	(0.83)
M/B ratio$_{t-1}$	-0.011**	-0.013***	-0.012*	-0.009***	-0.005	-0.027***	0.008	-0.002
	(-2.12)	(-6.65)	(-1.69)	(-3.61)	(-0.35)	(-2.90)	(0.33)	(-0.21)
ROA$_{t-1}$	-0.039***	-0.026***	-0.046**	-0.021**	0.299*	0.073	0.511**	0.180
	(-2.64)	(-3.89)	(-2.56)	(-2.41)	(1.81)	(0.85)	(1.99)	(1.58)
Tangibility$_{t-1}$	0.084	0.034	0.195***	0.064	-0.172	0.091	-0.235	0.101
	(1.33)	(0.88)	(2.73)	(1.34)	(-1.06)	(0.46)	(-1.00)	(0.53)
Dividend$_{t-1}$	-0.005	0.004	0.003	0.005	-0.051	-0.048	-0.051	-0.058**
	(-0.41)	(0.41)	(0.19)	(0.42)	(-0.67)	(-1.49)	(-0.56)	(-2.04)
AZ$_{t-1}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.012**	-0.007**	-0.030***	-0.023***
	(-3.78)	(-13.85)	(-3.50)	(-8.75)	(-2.36)	(-2.20)	(-3.12)	(-4.88)
ELS$_{t-1}$	0.001	0.001*	0.001	0.001**	-0.018	-0.003	-0.031	-0.007
	(1.33)	(1.66)	(1.03)	(2.39)	(-0.97)	(-0.23)	(-1.32)	(-0.48)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC2×Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	6102	6102	6102	6102	251	251	251	251
Adj. R2	0.172	0.283	0.155	0.206	0.430	0.467	0.374	0.488

Panel C: Placebo Tests

	Book	Mkt	Net Book	Net Mkt	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated (Placebo) × Post	0.020**	0.003	0.023*	0.006	0.007	-0.004	0.012	-0.000
	(2.06)	(0.45)	(1.92)	(0.72)	(0.69)	(-0.56)	(0.99)	(-0.04)
Log(Assets)_{t-1}	0.028**	0.027***	0.050***	0.028***	0.030**	0.033***	0.051***	0.032***
	(2.32)	(3.85)	(3.47)	(3.18)	(2.53)	(4.79)	(3.44)	(3.61)
M/B ratio_{t-1}	-0.012**	-0.014***	-0.012*	-0.009***	-0.011**	-0.012***	-0.012*	-0.009***
	(-2.30)	(-6.48)	(-1.79)	(-3.82)	(-2.06)	(-6.34)	(-1.66)	(-3.51)
ROA_{t-1}	-0.041***	-0.023***	-0.045**	-0.017*	-0.040***	-0.025***	-0.046**	-0.020**
	(-2.69)	(-3.02)	(-2.49)	(-1.85)	(-2.64)	(-3.73)	(-2.53)	(-2.30)
Tangibility_{t-1}	0.089	0.035	0.203***	0.061	0.089	0.031	0.207***	0.061
	(1.39)	(0.89)	(2.87)	(1.28)	(1.37)	(0.81)	(2.79)	(1.24)
Dividend_{t-1}	0.009	0.014	0.015	0.015	-0.002	0.006	0.004	0.007
	(0.76)	(1.38)	(0.96)	(1.16)	(-0.19)	(0.63)	(0.26)	(0.57)
AZ_{t-1}	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.86)	(-13.49)	(-3.58)	(-9.37)	(-3.67)	(-13.35)	(-3.42)	(-8.69)
ELS_{t-1}	0.001	0.000	0.001	0.001**	0.001	0.001	0.001	0.001**
	(1.43)	(1.41)	(1.02)	(2.56)	(1.31)	(1.57)	(1.01)	(2.36)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC2×Year FE					Y	Y	Y	Y
N	5926	5926	5926	5926	5926	5926	5926	5926
Adj. R2	0.099	0.151	0.105	0.117	0.170	0.281	0.153	0.204