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Local Labor Market Competition and Capital Structure Decisions

John (Jianqiu) Bai
Northeastern University, j.bai@northeastern.edu

Massimo Massa
INSEAD, Massimo.massa@insead.edu

Chi Wan
University of Massachusetts Boston, chi.wan@umb.edu

Yan Wang
McMaster University, ywang@mcmaster.ca

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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 competition. We find that firms hiring in more competitive labor markets tend to have lower financial leverage. To establish causality, we exploit the establishment of Amazon HQ2 in Crystal City, Virginia as an exogenous shock to the local labor market competition, and find results that are consistent with our baseline result. Furthermore, the negative relation between labor market competition and leverage is more pronounced when the firm competes for high-skilled labor, high-paid jobs, and in the geographical regions with low GDP growth.

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All errors and omissions are our own.

Introduction

A large literature has studied the economic role played by the degree of competition 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 less competitive 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 lower degree of labor market competition – can arise from labor market frictions such as frictions 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 competition exhibits substantial time-series changes (Benmelech et al. 2020, Autor, Dorn, Katz, Petterson, and Van Reenen 2020) as well as geographical variation: Rinz (2018)

[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).

and Hershbein, Macaluso, and Yeh (2019) point out that, unlike the national labor market competition, local labor market competition has generally been increasing by at least 25% since 1976.[3]

Labor market competition, 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 competition 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 competition 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 competition.

This paper attempts to fill this gap by studying how local labor market competition shapes firms' financial policies using a novel dataset that tackles empirical difficulty. In theory, there are at least three different reasons how local labor market competition can impact firms' capital structure. First, local labor market competition, by limiting the bargaining power of the employers and allowing workers to negotiate higher wages, will reduce profitability and lower the firm's incentives to borrow to get tax shields. Second, the higher bargaining power of employees will allow employees to demand a higher wage premium for bearing the financial distress risk, increasing the indirect costs of financial distress. Indeed, 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), further reducing the incentive to lever.[4] Third, the higher bargaining power of the employees will reduce the firm's "flexibility"

[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

to cut down wages and discharge workers, effectively increasing the proportion of fixed costs relative to variable costs (i.e., its operating leverage). Higher operating leverage raises the costs associated with financial distress risk for a given level of debt (e.g., restructuring costs) and incentivizes the firms to adopt a more conservative financial policy (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 competitive local labor market leads firms to adopt a more conservative financial policy.

While the theory is simple, 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 competition that has sufficient time series and cross-sectional variation. We overcome this issue by exploiting a "big data" repository of U.S. employer's 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-commuting zone (CZ)-skill (SOC) cluster, a measure of local labor market competition 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-

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that employees with higher ability are more likely to leave a company approaching bankruptcy than an average employee.

[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).

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 competition then aggregates the hiring-weighted local labor market competition measure [1 − Herfindahl-Hirschman Index (HHI)] across the dimensions of commuting zone and skill cluster. In this case, Firm A, with higher exposure to local labor competition than Firm B, is expected to have lower financial leverage.

This measure has several distinct advantages in capturing local labor market competition 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 the product market competition. BGT data, which provides detailed information on the employer, job title, and job location, allows us to construct a more refined local labor market competition 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 competition in the U.S. (Azar, Marinescu, and Steinbaum 2019, 2020).[8]

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

[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.

market will also depend on their ability to attract specialized labor. This traditionally creates a very complex endogeneity issue. We overcome the endogeneity 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, we further distinguish the effect of the labor market competition independently of the product market competition by focusing on an experiment that only affects the labor market but not the product market. This is the establishment of Amazon HQ2 in Crystal City, Arlington, Virginia. 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 competition.

We test our hypothesis using a sample of 13,462 firm-year observations over the period from 2007 to 2019. Our main finding is that firms with a higher degree of labor market competition have lower financial leverage. In terms of economic effect, an increase in one standard deviation of local labor market competition is correlated with a 0.4% (0.5%) decrease in book leverage (market leverage), which implies a 1.6% (2.8%) decrease 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). This finding supports our working hypothesis that firms hiring in more competitive local labor markets have a

[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

limited negotiating power relative to their employees, and are forced to adopt a more conservative financial policy.

As mentioned above, one concern in this type of analysis is that the negative relation between labor market competition and firm leverage is endogeneity. Specifically, an unobservable omitted variable could affect both the labor market competition 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).

We lastly investigate the channel of the impact of labor market competition on firm leverage. The impact of labor market competition on firm leverage should be stronger for jobs that are less likely to substitute either because of their attributes – e.g., high-skilled labor – or because of firm characteristics – i.e., firm-specific training. We hypothesize that the negative relation between local labor market competition and financial leverage is more pronounced among the firms hiring jobs that are less likely to substitute and thus with higher employee negotiation power. A typical example would be high-skilled labor that has 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) and high-salary labor who are more costly to replace (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 competition on financial leverage is stronger among these occupations. Furthermore, a higher local labor market competition can strengthen the workers' bargaining position in negotiating employment and wages in the geographical regions with limited growth opportunities and labor inflows. We find that the negative relationship between local labor market competition and financial leverage is more pronounced in the geographical regions that experience lower growth.

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 study, therefore, highlights the real impact of labor market competition on firms' financial policy.

Our paper also relates to a large literature in labor economics that investigates labor market power. Many studies find robust evidence of the existence of local labor market concentration/competition on wages and employment (e.g., Dube, Jacobs, Naidu, and Suri 2018; Benmelech et al., 2020). More specifically, 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 competition measure at different geography and location clusters and investigating the effect of local labor market competition 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, construction of analytical 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 U.S. public firms are obtained from Compustat. Following prior studies on capital structure (e.g., Simintzi, Vig, and Volpin 2015), we exclude firms in the financial industry (SIC codes 6000 – 6999) and utilities industry (SIC codes 4900 – 4999). We also drop observations for which total assets or total sales are missing.

Second, we obtain information on local hiring for each firm from BurningGlass Technologies (BGT hereafter), which is 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). The database contains unique identifiers for each job posting, occupation, industry, geography (e.g., US commuting zones), as well as the name of the employer posting the job, and skill and knowledge requirements. For our purpose, the detailed geographic information and the skill categories allow us to construct a local labor market competition measure at a highly granular level, e.g., commuting zone (CZ)-skill (SOC) level. We then aggregate this local labor market competition measure into a firm-level measure across all commuting zone-skill categories in which the firm hires in a given year. The detailed procedure of this calculation is provided in section 2.2.

Lastly, we conduct a two-step matching process between Compustat and BGT to construct our final sample. We first use fuzzy matching techniques to match both databases based on the parent firm and its subsidiary names. Then we manually check the quality of these matches and then cross-validate among the researchers. Our final analytical sample consists of 13,462 firm-year observations, corresponding to 2,313 unique Compustat firms.

2.2 Local labor market competition (LLMC)

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.[10] 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 of employment concentration at the U.S. county-industry (4-digit SIC) level.

However, Census data does not allow for constructing the HHI at the occupational level. To compute an occupational-level labor market power, Qiu and Sojourner (2019) estimate the occupational distribution of employment with 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 near universe of 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.[11] In terms of occupation composition, as pointed out 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.[12]

[10] 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) market, which implies that both labor market concentration and labor supply elasticity measure employer power.

[11] 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.

[12] There are a couple of characteristics of BGT job vacancies. First, 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;

In this paper, we follow the construction of Azar et al. (2020) of the local labor market competition. To construct a firm-level labor market competition, 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 competition for each pair of Commuting Zone (CZ)-skill clusters. This allows for a comprehensive and disaggregated measure of local labor market competition at the occupational level across a large group of industries.

Specifically, to measure a firm i's exposure to local labor market competition, 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,

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

second, BGT cleans the duplicated listings if it collects the same job posts from various platforms; third, BGT provides the job vacancy listings regardless whether and when the job posts have been fulfilled, all of which allow us to construct a cleaner measure of labor market competition that is less likely to subject to endogenous employer-employee matching process.

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

To measure a firm's overall exposure to local labor market competition, 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 Competition (LLMC) as:

$$LLMC_{i,t} = 1 - \sum_m \omega_{i,m,t} \times HHI_{m,t} = 1 - \sum_m \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}. \tag{3}$$

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

In Table 1, we report the mean, median, the 25th, the 75th percentiles, and standard deviation of the local labor market competition measure (LLMC). The average value of our firm-level LLMC measure is 0.929 with a standard deviation of 0.082.

To illustrate the evolution of the local labor market competition over the sample period, we plot the changes in LLMC from 2010 to 2018 across the U.S. commuting zones for occupation "computer programmers" (SOC:15-1131). The darker color indicates intense hiring and the lighter color indicates mild hiring. We see that the demand for computer programmers varies widely across geographical regions. For example, the most competitive local labor markets for computer programmers are the Northeast Regions, like Boston-Cambridge-Newton and New York-Newark-Jersey City, regions near the Great lakes like Grand Rapids-Kentwood and Chicago-Naperville-Elgin, and California regions like San Francisco-Oakland-Berkeley, Santa Maria-Santa Barbara, and Los Angeles-Long Beach-Anaheim. By comparing the figure in 2010 to the figure in 2018, we observe that the market shows an increasing demand for computer programmers over time across all geographical regions.

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 panels A and B of Table 1, respectively. 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 27.29% (17.25%). An average firm holds 1080.5 million total assets and has a market-to-book ratio of 2.626. On average, there is 42.35% of firm-year observations where dividends are paid. The average ROA and tangibility of a firm are 0.035 and 0.233 respectively in our sample. On average, a firm has a modified Atlamn z-score of 2.069 and an extended labor share of 0.682.

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 competition and financial leverage. In Section 3.2, we use the construction of Amazon's second headquarter (HQ2) in Crystal City as a quasi-natural experiment to local (incumbent) firms' local market competition. In Section 3.3, we examine how the impact of labor market competition on firm leverage varies with employees' bargaining power to shed more light on the underlying mechanism.

3.1 Baseline results

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

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

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 competition measure in Equation (3). The main coefficient of interest is β, which measures the correlation between labor market competition 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, and finally, a local market fixed effect (φ_m) to control for the effect of local labor market conditions or local market economic fundamentals. The local market is defined as the commuting zone (CZ) of the firm's headquarters. $X_{i,t-1}$ is the vector of firm-level controls and includes previously known determinants of a firm's capital structure. These include firm size, book-to-market ratio, ROA, tangibility, dividend, modified Altman-*z* score, and extended labor share. A detailed definition of these variables is discussed in section 2.3. Standard errors are clustered at the firm level.

Columns 1-4 of Table 2 report the baseline results on the relation between local labor market competition and financial leverage. Our results show consistent negative coefficients on LLMC across all the four different measures of financial leverage. For example, coefficients associated with LLMC range from -0.038 to -0.053, and all are statistically significant across the different specifications. These findings are consistent with our hypothesis that a competitive labor market shifts the bargaining power from employers to workers, which leads firms to adopt a more conservative capital structure.

Previous studies (e.g., MacKay and Phillips 2005) find that different industries exhibit notable differences in their capital structure. 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. 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 an industry×year fixed effect in Equation (4) to account for any time-varying industry dynamics and report these results in columns (5) to (8) of Table 2. In this more stringent specification, our documented negative relation between local labor market concentration and a firm's leverage ratio becomes statistically more significant and economically stronger. For example, in the fully saturated model with industry x year fixed effects, an increase in one standard deviation of local labor market competition is correlated with a 0.4% (0.5%) decrease in book leverage (market leverage), which corresponds to approximately 1.6% (2.8%) relative to the sample mean.

The results in Table 2 use the entire BGT coverage, which includes a gap between 2007 and 2010. In untabulated results, we re-estimate our baseline specifications (i.e., equation (4)) by excluding the year 2007. This addresses the concern 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). Overall, our results remain unchanged if we exclude the year 2007.

3.2 Establishing causality

3.2.1 Amazon HQ2: the empirical setting

So far, our documented negative relation 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 competition 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 higher local market competition. 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 competition 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, such as the local labor market fixed effect and industry-times-year fixed effect to control for any location-specific variation or any time-variant industry 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 competition.

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 competition 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, with the intention 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,[13] 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 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.[14] We employ Amazon HQ2 expansion as our primary empirical setting to establish causality.

[13] 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.

[14] 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,

There are several reasons why the Amazon HQ2 expansion serves as an ideal laboratory. First, the skill categories in 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 competition 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 increase in the local market competition 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.[15] 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* relationship between local labor market competition and a firm's financial leverage. For example, one such positive externality is that Amazon's entry into Crystal City attracts people to move into the region, leading to an appreciation in 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

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

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

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 with no concern for any confounding effect from the product market.

3.2.2 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%.[16]

Given that these firms have a similar demand for skills in their labor force, they face a significant increase in their local labor market competition after Amazon enters the region. The intuition is that for these skill categories, the local labor market competition has significantly increased 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.

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

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 3, 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:

$$Leverage_{i,t} = \beta Treated_i \times Post_t + \gamma' X_{i,t-1} + \alpha_i + \tau_t + \varphi_m + \varepsilon_{i,t}, \tag{5a}$$

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 3. 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.

3.2.3 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 4. 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 negative relation between local labor market competition 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:

$$\begin{aligned} Leverage_{i,t} &= \theta_1[Treated_i \times AmazonHQ2\,year(-2)] \\ &+ \theta_2[Treated_i \times AmazonHQ2\,year(-1)] \\ &+ \theta_3[Treated_i \times AmazonHQ2\,year(+1)] + \gamma' X_{i,t-1} + \alpha_i + \tau_t + \varphi_m + \varepsilon_{i,t}, \end{aligned} \tag{5b}$$

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 4, 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 2, 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 competition 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.[17] 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.[18]

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

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

market competition 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 (5a) using the placebo "treated" and "control" firms.

We report our results in Panel C of Table 4. 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 high-tech firms hiring mainly technology people and firms hiring from different talent pools but rather by the changes in local labor market competition brought about by Amazon's HQ2 entry.

3.3 Cross-sectional tests

In this section, we explore the mechanism through which the local labor market competition affects financial leverage. The bargaining power of workers varies systematically by occupation or skill level. For example, Schubert et al. (2020) show a large heterogeneity in labor market competition 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 negative impact of local labor market competition on financial leverage is driven by the changes in the relative bargaining power of employees vs employers, we test the cross-sectional within-market variation in the negative relation between the local labor market competition and financial leverage across a few occupation characteristics that are indicative of different employee bargaining power.

3.3.1 Skilled workers

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 low-skilled jobs and shifted labor demand toward the 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, the low-skilled workers suffer from a greater disadvantage in relative bargaining power in negotiating wages and employment with employers than high-skilled labor due to their high substitutability by automation technologies. By contrast, high-skilled workers enjoy a higher bargaining power in the local labor market due to the scarcity of their skills. Following these arguments, if an increase in local labor market competition limits an employer's bargaining position and consequently constrains a firm's use of financial leverage, then we should expect that such a situation is more devastating for firms that hire high-skilled labor with low substitutability and high bargaining power.

In order to capture the relative bargaining power of workers to firms, following the prior literature (Deming 2017; Hershbein and Kahn 2018; Deming and Kahn 2018), we classify the occupations into high-skilled occupations and low-skilled occupations. We refine our LLMC measure based on the subgroup of STEM and non-STEM occupations. STEM (abbreviation for Science, Technology, Engineering, and Mathematics) job classification is defined to consist of 100 occupations including computer and mathematical, architecture and engineering, life and physical science occupations, as well as managerial and postsecondary teaching occupations related to these functional areas and sales occupations requiring scientific or technical knowledge at the postsecondary level. The list of STEM occupations is compiled by the Occupational Employment Statistics (OES) program in the U.S. Bureau of Labor Statistics (BLS).[19]

We split LLMC based on whether or not an occupation has a STEM designation, and the STEM component is defined as follows. The non-STEM component ($SOC \notin STEM$) is defined in parallel.

$$LLMC_{i,t}^{STEM} = 1 - \sum_{m:\mathrm{SOC}\in\mathrm{STEM}} \omega_{i,m,t} \times HHI_{m,t} = 1 - \sum_{m:\mathrm{SOC}\in\mathrm{STEM}} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}. \tag{6a}$$

$LLMC^{STEM}$ is the weighted sum of local labor HHI across all local labor markets (m defined at the SOC-CZ level) where the SOC code has a STEM designation. The two components add up to our primary proxy (LLMC; with a difference of one). We then repeat our regression analysis in equation (4) using the decomposed LLMC measure based on STEM occupation classification.

The results are reported in Table 5. They show that the coefficients for $LLMC_{i,t}^{STEM}$ are all larger than the coefficients for $LLMC_{i,t}^{non-STEM}$. For instance, for the specifications using the book leverage (market leverage) as the dependent variable, the coefficient for $LLMC_{i,t}^{STEM}$ is -0.108 (-0.104) with a *t*-statistic of -2.14 (-3.06). By contrast, the coefficients for $LLMC_{i,t}^{non-STEM}$ are only –0.085 (–0.055) with *t*-statistics of –2.07 (–2.01), respectively. Consistent with our conjecture, our findings suggest that the effect of local labor market competition on financial leverage is more evident among the high-skilled occupations that have a stronger bargaining position in negotiating wages and employment.

3.3.2 Labor costs

Recent literature on labor economics generally finds a significant negative relation between local labor market concentration and employment/wages (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). These findings suggest that higher wages of employees in a more competitive local labor market arise from the fact that workers have access to more outside options and possess stronger bargaining positions in negotiating employment and wages. Therefore, we expect that the effect of local labor market competition

[19] See the list of STEM occupations here: https://www.onetonline.org/find/stem?t=0

on financial leverage is stronger for firms that operate in the local labor market with a high average wage cost since these firms suffer more from labor-adjustment costs and thus have a weaker bargaining position relative to their employees. Following this argument, we separate our sample using the average occupational wages at the state level.

We obtain the occupation-level wages at the state level from the Occupational Employment and Wage Statistics (OEWS) program in the U.S. Bureau of Labor Statistics (BLS). Then we partition occupations in the local labor markets by their annual median wage estimates. Specifically, we decompose LLMC based on whether an occupation has an annual wage estimate higher or lower than the local labor market median. The high-salary component is specified as follows

$$LLMC_{i,t}^{High\ salary} = 1 - \sum_{m:\mathrm{SOC-CZ} \in \mathrm{High\ salary}} \omega_{i,m,t} \times HHI_{m,t}$$

$$= 1 - \sum_{m:\mathrm{SOC-CZ} \in \mathrm{High\ salary}} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}. \qquad \text{6b)}$$

In other words, $LLMC_{i,t}^{High\ salary}$ ($LLMC_{i,t}^{Low\ salary}$) is defined as the weighted sum of local labor HHI across all local labor markets (i.e., m defined at the SOC-CZ level) where the SOC code has an average occupational wage higher (lower) than the median occupational wage in the local labor market. Next, we repeat our regression analysis in equation (4) using the $LLMC_{i,t}^{High\ salary}$ and $LLMC_{i,t}^{Low\ salary}$ as our variable of interest.

Our results are presented in Table 6. We observe that the coefficients for $LLMC_{i,t}^{High\ salary}$ are consistently negative and statistically significant at the 5% level, regardless of the leverage ratio considered; while the coefficients for $LLMC_{i,t}^{Low\ salary}$ are either weakly significant or insignificant. For example, the coefficient for $LLMC_{i,t}^{High\ salary}$ in the specification using book leverage as a dependent variable is -0.084 and highly significant with a *t*-statistic of -2.27, which is more than 35% higher than the coefficient for $LLMC_{i,t}^{Low\ salary}$(coef. = –0.054, statistically insignificant with a *t*-statistic of -1.33). These findings indicate that, indeed, for firms operating in the local labor market with a high average labor cost (i.e., high salary), their capital structure decisions tend to be more responsive to the change in labor market competition compared to those facing a lower average labor cost (i.e., low salary).

3.3.4 Geographic regions

Finally, the bargaining power of workers also varies across different geographical regions. The geographical regions that have slower growth and suffer more from job losses in the recssions were induced to restructure their production toward greater use of technology and high-skilled worker (Hershbein and Kahn 2018). Also, the regions with limited GDP growth attract less talents into the local labor market, which further reduce the labor supply and intensify the local labor market competition. Therefore, we expect the negative relationship between local labor market competition and financial leverage across to be more pronounced in geographical areas with slower GDP growth.

To measure the economic condition of each local labor market (m is defined at the CZ), we compute the annual GDP growth rate across all counties. We then partition LLMC by the annual median GDP growth rate across all counties, as follows,

$$LLMC_{i,t}^{High\ (low)\ GDP} = \sum_{m:CZ \in High\ (low)\ GDP} \omega_{i,m,t} \times HHI_{m,t} = \sum_{m:CZ \in High\ (low)\ GDP} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t},$$

where the local labor markets are partitioned by the annual median GDP growth rate. Next, we repeat our regression analysis in equation (4) using the $LLMC_{i,t}^{High\ GDP}$ and $LLMC_{i,t}^{Low\ GDP}$ as our variable of interest.

We present our results in Table 7. As indicated in Table 7, the coefficients for $LLMC_{i,t}^{Low\ GDP}$ are persistently negative and statistically significant while the coefficients for $LLMC_{i,t}^{High\ GDP}$ are either weakly positive or insignificant. For example, the coefficient for $LLMC_{i,t}^{Low\ GDP}$ is -0.065 and significant at the 5% level (*t*-statistic = 2.17) and the coefficeint for $LLMC_{i,t}^{High\ GDP}$ is 0.006 and statistically insignificant (*t*-statistic = 0.92) in the specification of book leverage. Our findings indicate that the negative impact of local labor market competition on the firms' use of financial leverage is more pronounced in the geographical regions with limited labor inflows.

Conclusion

In this paper, we analyze the impact of labor market competition on firms' capital structure decisions. Using the near universe of online job postings between 2007 and 2019, we find a robust and significant negative association between labor market competition and leverage ratios.

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 negative relationship between labor market competition and firm leverage is likely causal.

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 negative impact of labor market competition on firm leverage is most pronounced for high-skilled workers, high-salary jobs, and in the geographical region with slow GDP growth. Taken together, these results suggest that workers' bargaining power relative to firms is likely to be the underlying economic mechanism through which the effect operates.

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. Local labor market competition of computer programmers (SOC 15-1131)
The two figures show the level of local labor market competition (1-$HHI_{m,t}$ defined in equation (2)) across commuting zones in 2010 and 2018 for the occupation of computer programmers (SOC-6 occupation code 15-1131).

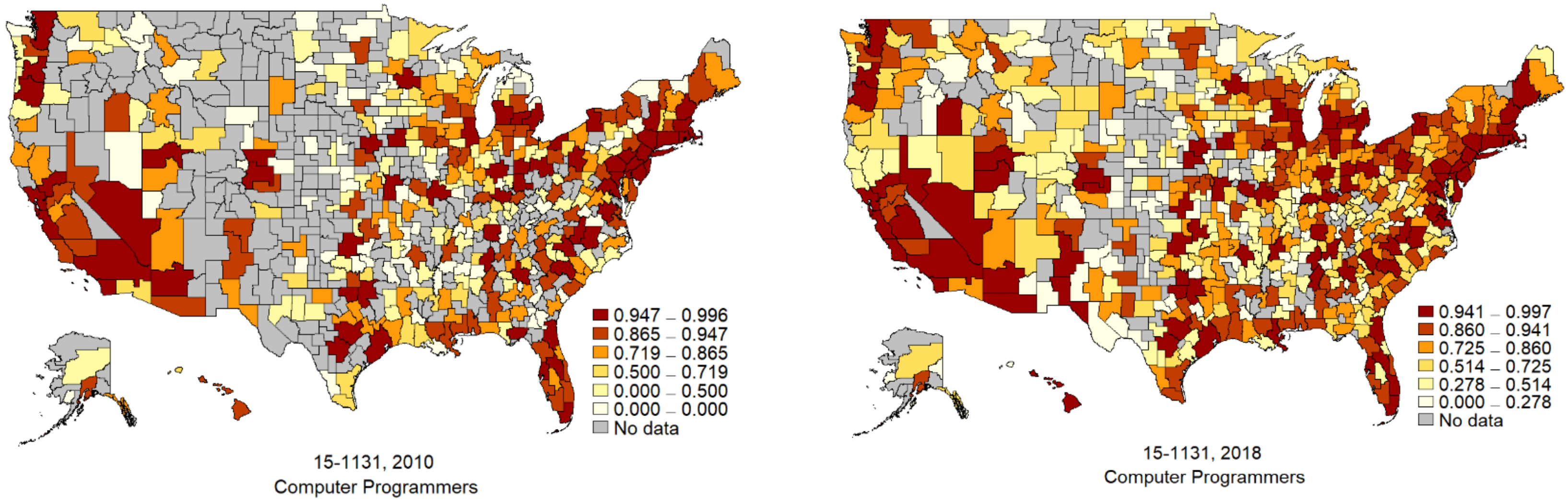

Figure 2. Amazon's HQ2 Difference-in-Difference Analysis: Parallel Trend
This figure displays estimated coefficients of the tests on the treated firms' adjustment on their leverage ratios in response to Amazon's entry relative to the control firms. Specifically, it displays the time series of coefficient 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 4, 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 4, 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 4, Panel B.

Panel A: Full Sample

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

Table 1. Summary Statistics

Panel A presents the descriptive statistics of the dependent 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.

Panel B presents the descriptive statistics of the independent variables. A firm's exposure to local labor market competition (LLMC) is as defined in section 2.2. 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	13,462	0.2729	0.2427	0.0846	0.2376	0.3913
Mkt	13,462	0.1725	0.1646	0.0393	0.1325	0.2547
Net Book	13,462	0.0984	0.3494	-0.1100	0.1204	0.3133
Net Mkt	13,462	0.0808	0.2173	-0.0468	0.0679	0.2009

Panel B: Summary Statistics for LLMC and control variables

	N	Mean	STD	25th	Median	75th
LLMC	13,462	0.929	0.082	0.913	0.954	0.978
Log(at)	13,462	6.985	2.110	5.699	7.084	8.372
M/B	13,462	2.616	10.520	1.220	1.645	2.460
ROA	13,462	0.035	0.814	0.065	0.115	0.163
Tangibility	13,462	0.233	0.2171	0.070	0.156	0.332
dividend	13,462	0.424	0.494	0.000	0.000	1.000
AZ	13,462	2.069	29.790	1.710	3.151	4.923
ELS	13,462	0.682	0.767	0.514	0.705	0.881

Table 2. Baseline Results

This table presents regression results of leverage ratios on a firm's exposure to local labor market competition 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 columns (1)-(4) include 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 variables are as defined in Table 1. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	Book	Mkt	Net Book	Net Mkt	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LLMC	-0.038*	-0.041***	-0.044*	-0.053***	-0.052**	-0.055***	-0.056**	-0.062***
	(-1.78)	(-2.59)	(-1.67)	(-2.68)	(-2.32)	(-3.32)	(-2.04)	(-3.05)
Log(at)	0.028***	0.039***	0.065***	0.045***	0.028***	0.042***	0.065***	0.045***
	(4.10)	(8.75)	(7.81)	(7.86)	(4.10)	(9.51)	(7.50)	(7.84)
M/B	-0.001*	-0.002	-0.002	-0.001	-0.001	-0.002	-0.002	-0.001
	(-1.67)	(-1.60)	(-1.52)	(-1.05)	(-1.54)	(-1.51)	(-1.49)	(-1.00)
ROA	-0.050**	-0.040**	-0.061**	-0.028**	-0.047*	-0.038**	-0.062**	-0.029**
	(-1.97)	(-2.51)	(-2.34)	(-2.18)	(-1.87)	(-2.50)	(-2.32)	(-2.23)
Tangibility	0.079	0.114***	0.239***	0.181***	0.071	0.101***	0.228***	0.162***
	(1.45)	(3.81)	(3.78)	(4.64)	(1.26)	(3.31)	(3.43)	(3.93)
dividend	0.005	0.001	0.015	0.014*	0.002	0.002	0.011	0.011
	(0.61)	(0.26)	(1.47)	(1.89)	(0.28)	(0.35)	(1.06)	(1.57)
AZ	-0.000***	-0.000	-0.000**	-0.000	-0.000***	-0.000	-0.000**	-0.000
	(-3.74)	(-1.34)	(-2.37)	(-1.33)	(-3.59)	(-1.27)	(-2.17)	(-1.15)
ELS	0.002	0.001	0.002	0.002*	0.002	0.001	0.002	0.002*
	(1.49)	(1.37)	(1.24)	(1.70)	(1.45)	(1.43)	(1.21)	(1.72)
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
NNN	13462	13462	13462	13462	13462	13462	13462	13462
Adj R2	0.119	0.134	0.134	0.122	0.159	0.218	0.159	0.172

Table 3. 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 variables are as defined in Table 1. 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 (1)	Mkt (2)	Net Book (3)	Net Mkt (4)	Book (5)	Mkt (6)	Net Book (7)	Net Mkt (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(at)	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	-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	-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	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	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	-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	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 4. 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 (5b). 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 variables are as defined in Table 1. 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(at)	-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	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	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	-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	-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	-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	-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(at)	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	-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	-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	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	-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	-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	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(at)	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	-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	-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	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	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	-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	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

Table 5. Heterogeneity: High-skilled vs. low-skilled labor

This table evaluates the differential effect of a firm's exposure to the competition of a high-skilled vs. a low-skilled local labor market. A firm's overall exposure to local labor market competition (LLMC) is split based on whether or not an occupation has a STEM designation and the STEM component is defined as below. The non-STEM component ($SOC \notin STEM$) is defined in parallel.

$$LLMC_{i,t}^{STEM} = 1 - \sum_{m:\text{SOC}\in\text{STEM}} \omega_{i,m,t} \times HHI_{m,t} = 1 - \sum_{m:\text{SOC}\in\text{STEM}} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}.$$

$LLMC^{STEM}$ is the weighted sum of local labor HHI across all local labor markets (m defined at the SOC-CZ level) where the SOC code has a STEM designation. The list of STEM occupations is compiled by the Occupational Employment Statistics (OES) program in the U.S. Bureau of Labor Statistics (BLS). The specification follows equation (4) but uses the decomposed high-skilled vs. low-skilled LLMCs based on STEM designations. 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 variables are as defined in Table 1. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)
$LLMC^{STEM}$	-0.108**	-0.104***	-0.112	-0.137***
	(-2.14)	(-3.06)	(-1.64)	(-2.98)
$LLMC^{non-STEM}$	-0.085**	-0.055**	-0.099**	-0.061*
	(-2.07)	(-2.01)	(-1.99)	(-1.73)
Other 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
N	10800	10800	10800	10800
Adj. R2	0.179	0.238	0.179	0.192

Table 6. Heterogeneity: High v.s low SOC-salary

This table evaluates the differential effect of a firm's exposure to the competition of a high-salary vs. a low-salary local labor market. A firm's overall exposure to local labor market competition (LLMC) is split based on whether an occupation has an annual wage estimate higher or lower than the local labor market median. The high-salary component is specified as follows,

$$LLMC_{i,t}^{High\ salary} = 1 - \sum_{m:\text{SOC}-\text{CZ}\in\text{High salary}} \omega_{i,m,t} \times HHI_{m,t}$$

$$= 1 - \sum_{m:\text{SOC}-\text{CZ}\in\text{High salary}} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t}.$$

$LLMC_{i,t}^{High\ salary}$ ($LLMC_{i,t}^{Low\ salary}$) is defined as the weighted sum of local labor HHI across all local labor markets (i.e., m defined at the SOC-CZ level) where the SOC code has an average occupational wage higher (lower) than the median occupational wage in the local labor market. The specification follows equation (4) but uses the decomposed high-salary vs. low-salary LLMCs based on the average occupational wages in the local market. 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 variables are as defined in Table 1. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)
$LLMC^{high\ salary}$	-0.084**	-0.069***	-0.132***	-0.101***
	(-2.27)	(-2.75)	(-2.86)	(-3.05)
$LLMC^{low\ salary}$	-0.054	-0.063**	-0.059	-0.075**
	(-1.33)	(-2.10)	(-1.23)	(-2.12)
Other 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
N	10082	10082	10082	10082
Adj. R2	0.213	0.265	0.212	0.221

Table 7. Heterogeneity: Geographical regions

This table evaluates the differential effect of a firm's exposure to the local market competition in geographical regions with high- and low- GDP growth. LLMC is partitioned by the annual median GDP growth rate across all counties, as follows,

$$LLMC_{i,t}^{High\ (low)\ GDP} = \sum_{m:CZ\in High\ (low)\ GDP} \omega_{i,m,t} \times HHI_{m,t} = \sum_{m:CZ\in High\ (low)\ GDP} \frac{V_{i,m,t}}{V_{i,t}} \times HHI_{m,t},$$

The specification follows equation (4) but uses the decomposed LLMCs based on high- vs. low- GDP growth rate in the local markets. 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 variables are as defined in Table 1. Standard errors are clustered at the firm level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)
$LLMC^{high\ GDP\ growth}$	0.006	0.009**	0.014	0.013**
	(0.92)	(2.02)	(1.56)	(2.17)
$LLMC^{low\ GDP\ growth}$	-0.065**	-0.066***	-0.075**	-0.065**
	(-2.17)	(-2.88)	(-2.04)	(-2.34)
Other 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
N	11343	11343	11343	11343
Adj. R2	0.190	0.244	0.187	0.201