Labor Market Power and Financial Leverage: Evidence from Online Job Postings

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Abstract

Using the near universe of online job postings from 2007 to 2021, we construct a firm-level metric of labor market power. We find that firms with higher labor market power tend to have higher financial leverage. Our findings are not driven by product market competition or correlated labor market characteristics. The evidence is less pronounced among firms hiring in occupations with high labor mobility and skill transferability. To establish causality, we exploit the establishment of Amazon HQ2 in Crystal City as a shock to the labor market power of local firms and show consistent findings with our baseline results.

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I. Introduction

There are ongoing concerns and policy debates about market power and its potential effects on the labor market dynamics.[1] A few large employers dominating the labor market (i.e., monopsonists) can exercise their market power to drive down workers' wages, decrease output, and widen wage inequality. The labor market power of employers can stem from labor market frictions associated with job search, geographic mobility, non-compete or no-poaching agreements, as well as heterogeneous preferences over job characteristics. Recently, scholars urged more rigorous antitrust enforcement against anticompetitive labor practices. The White House, the Department of Justice (DOJ), the Federal Trade Commission (FTC), and the Treasury Department have all expressed interest in exploring potential antitrust measures to counteract employers' labor market power.[2]

Prior literature on labor economics has primarily focused on the effect of labor market power ("monopsony") on aggregated labor market outcomes. It argues that labor markets dominated by a few large employers limit workers' outside options, thereby enhancing the wage-setting power of incumbent firms. For example, recent studies show that the employer labor market power can suppress equilibrium wages by limiting the workers' alternative job options (Azar, Marinescu, Steinbaum, and Taska (2020), Benmelech, Bergman, and Kim (2020), Qiu and Sojourner (2023), Webber (2015), Rinz (2018), Prager and Schmitt (2021)), increases wage inequality (Webber (2015), Rinz (2018)), changes the demand for different types of labor skills (Yeh, Macaluso, and Hershbein (2022), Deming and Kahn (2018), Hershbein and Kahn (2018), Deming and Noray (2020)), and constrain labor mobility (Sokolova and Sorensen (2018),

[1] Yeh, Macaluso, and Hershbein (2022) find that the monopsony power in the US labor market decreased between the late 1970s and the early 2000s but has been sharply increasing since.
[2] See CRS report "Antitrust Issues in Labor Markets", https://crsreports.congress.gov/product/pdf/LSB/LSB10725/2.

Krueger and Ashenfelter (2018)). While prior research primarily focuses on aggregated labor market outcomes of monopsony power, recent studies also examine firm-level behavior. For instance, Benmelech et al. (2020) use disaggregated plant-level data from the U.S. Census Bureau to analyze the impact of labor market power on wages. Despite extensive research on labor market power, little attention has been given to its impact on the firm's financial policies. This paper attempts to fill this gap by examining how labor market power shapes a firm's financial policies.

Labor market power can impact firms' capital structure through two channels. First, labor market power allows firms to drive down equilibrium wages and enjoy higher profits. This, in turn, strengthens a firm's incentive to borrow for tax shields. Second, labor market power provides firms with more flexibility to cut down wages and discharge workers, which reduces labor rigidity and allows firms to increase financial leverage (Mandelker and Rhee (1984), Mauer and Triantis (1994), Kuzmina (2013), Simintzi, Vig, and Volpin (2015), Serfling (2016), Gustafson and Kotter (2022), Favilukis, Lin, and Zhao (2020)).[3] These considerations suggest that labor market power allows firms to adopt a more aggressive financial policy.

While the theory offers relatively clear predictions, empirical evidence on this topic remains scarce due to two key challenges. The first empirical hurdle is that measuring a firm's labor market power requires granular firm-level labor market data with sufficient time series and cross-sectional variation. The second empirical challenge is distinguishing the effect of labor market power from that of product market competition. We attempt to tackle these empirical

[3] For example, Simintzi et al. (2015) and Serfling (2016) find that operating leverage crowds out financial leverage in the setting of employment protection law changes. Gustafson and Kotter (2022) find that firms respond to minimum wage increase by decreasing their financial leverage. Favilukis, Lin, and Zhao (2020) find 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.

difficulties using a novel dataset of individual job postings and exploring a quasi-experiment that directly changes firms' labor market power.

We address the first empirical challenge by leveraging a big data repository of online job postings of U.S. employers from Lightcast (formerly Burning Glass Technology (BGT)).[4] These data cover nearly all online job postings from U.S. employers in 2007 and continuously from 2010 to 2021. Importantly, this comprehensive data source contains detailed geographic information on the location of hire, the occupation of each vacancy (SOC), the job title, the name of the employer, education, and knowledge requirements. The granularity of the dataset allows us to construct a firm-level measure of labor market power within each commuting zone (CZ) and skill (SOC) cluster. Specifically, we define the local labor market at the commuting zone (CZ) × skill (SOC) cluster and then measure a firm's labor market power (LMP) as the weighted average of its market share (i.e., fraction of job posts in a given local labor market) across all local labor markets in which it hires. A higher LMP indicates greater market power in wage-setting and more flexibility in adjusting labor costs.

Our measure of employer labor market power provides several advantages over existing measures based on data from the CareerBuilder.com or U.S. Census. The detailed information at the employer level provided by Lightcast data allows us to construct a firm-level measure of labor market power using a finer definition of the local labor market. In contrast, CareerBuilder.com has limited occupational coverage, which restricts its ability to capture labor market power across various local labor markets (Azar, Marinescu, and Steinbaum (2019, 2020)). Census data, while comprehensive, only reports employment at the commuting zone-

[4] Lightcast dataset has been used for several recent publications, including Deming and Kahn (2018), Hershbein and and Kahn (2018), Yeh, Macaluso, and Hershbein (2022), Schubert, Stansbury and Taska (2024), Azar et al. (2020), Deming and Noray (2020).

industry or county-industry level (Benmelech et al. (2020), Lipsius (2018), Rinz (2018)).[5] Moreover, such labor market power measures computed at the location-industry level can be highly correlated with product market competition, thus complicating our empirical analysis.

The second empirical challenge lies in the difficulty of isolating the effect of labor market power from that of product market competition, as employers hiring in the same labor market often compete in the same product market. For example, high-tech firms like Apple and Microsoft compete not only for specialized talents –i.e., computer engineers – but also for the similar products they offer – i.e., cloud computing. Apple's labor market power depends on labor demand from competitors, while its ability to compete in the product market relies on attracting specialized talent. This interdependence creates a complex endogeneity issue. We address this by leveraging Amazon HQ2's establishment in Crystal City, Arlington, Virginia, as an exogenous shock to the labor market power of incumbent firms.

Amazon HQ2's establishment provides an ideal setting for identification. First, the announcement of Amazon's HQ2 has a sizable impact on the local labor market, and its well-publicized timeline allows us to examine granular changes in incumbent firms' behavior around the announcement.[6] Second, the clearly defined job categories and skill requirements of the Lightcast dataset allow us to pinpoint the treatment and control firms competing directly with Amazon for skilled labor. Third, the announcement was largely unanticipated, which ensures that our results are not driven by incumbent firms adjusting financial leverage in anticipation of various externalities associated with Amazon HQ2's entry (e.g., tax credit or real estate

[5] 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.

[6] Amazon posted over 4,000 jobs in the Crystal City area one year after the announcement, with over one-third in its top five hiring occupations.

appreciation). Importantly, the Amazon HQ2 experiment allows us to isolate the effect of the labor market power from the product market interplay, given Amazon's internet sale model.

To establish the baseline, we test our hypothesis using a firm-level labor market power measure constructed from 15,294 firm-year observations between 2007 and 2021. Our main finding is that firms with greater labor market power tend to have higher financial leverage. A one standard deviation increase in labor market power correlates with a 0.94% (0.75%) increase in book (market) leverage, which corresponds to a 3.2% (3.4%) increase relative to the sample mean. This relation is robust to using alternative measures of leverage – i.e., market leverage, net book leverage, and net market leverage – and different specifications – i.e., controlling for the firm, year, the local market, and industry-times-year fixed effects.

Several further analyses confirm the robustness of our findings. The first potential concern is that the time-varying hiring weights assigned to different labor markets may create a spurious correlation between labor market power and the firm's financial leverage. We address this concern using fixed-weighted and employment-share-weighted labor market power measures and obtain similar results. The second potential concern is that the unobserved local economic and labor market conditions may correlate with our measure of labor market power and drive the increasing use of debts by firms. We find that our results remain robust after controlling labor market size (Kim (2020)) and commuting zone-times-year fixed effects. These findings suggest that employer labor market power is distinct from labor market size and other correlated local labor and economic factors. The third challenge in our analysis is the need to distinguish the effects of labor market power from those of product market power, as firms often compete for both talent and products within the same industry. While industry-times-year fixed effects help control broad industry-wide shocks, SIC industry codes may not accurately classify the firms into the same product market space. To address this issue, we first construct an alternative labor market power measure using only job postings from firms that do not compete in the same TNIC product market space as defined by Hoberg and Phillips (2010, 2015). Second, we use the original LMP measure but include product market-times-year fixed effects to control for time-varying product market dynamics. Our results remain robust, which confirms that the relationship between labor market power and financial leverage is not driven by the overlap between labor market and product market dynamics.

Once we have ascertained the robustness of our baseline results, we investigate whether the relationship between a firm's labor market power and its financial leverage depends on the type of talent it hires. If employers exploit labor market power to increase debt financing, this effect should be less evident for firms employing workers with greater outside options, such as those in high-mobility occupations or with transferable skills. Consistent with this hypothesis, we find that the positive relationship between a firm's labor market power and financial leverage is less pronounced among such firms.

Next, we move on to examine the mechanism that drives the positive relationship between employer labor market power and financial leverage. As discussed, firms may increase leverage due to tax shields from higher profits or greater flexibility in adjusting labor costs. If tax benefits from higher profits drive our findings, firms with greater labor market power should exhibit higher profits.[7] Alternatively, if reduced labor rigidity allows firms to adjust their labor costs more flexibly, we should observe lower earnings volatility of firms with greater labor market power and greater workforce downsizing in response to negative cash flow shocks. Our

[7] Prior studies (e.g., Graham 2000, Hennessy and Whited 2005) do not find robust evidence supporting the impact of profitability and tax benefits on financial leverage.

findings support the latter interpretation and indicate that a firm's labor market power affects its financial leverage primarily by reducing labor rigidity.

Finally, we address endogeneity concerns that the observed relationship between labor market power and firm leverage may stem from omitted variables or reverse causality. We exploit Amazon HQ2's establishment in Crystal City, Arlington, Virginia, as a quasi-experiment. Though this experiment offers numerous advantages, as explained, one empirical challenge is that the targeted location for Amazon's second headquarter is not random. Firms choose a location where their expected profits are highest, which are determined by a series of location-specific factors that are hard to control for, such as infrastructure, supply of workers with specific skills, and local regulatory environment (Greenstone and Moretti (2004)). To mitigate this concern, we follow Greenstone, Hornbeck, and Moretti (2010) and define firms in Crystal City and adjacent commuting zones as treated firms and those in New York City—the runner-up bidder that was chosen by Amazon but later withdrawn—as a counterfactual.[8] Furthermore, we find that Amazon's entry reduces treated firms' labor market power relative to control firms, leading to a significant decline in their financial leverage. Importantly, our results remain intact using a sample of local firms that compete with Amazon for skilled labor but do not compete in the product market. These findings further support a causal impact of a firm's labor market power on its financial leverage, and such an effect is likely driven by changes in the labor market power of incumbent firms rather than product market interactions.

[8] We do not compare the firms in winning city with all the rest of cities in U.S. due to unobserved heterogeneity between the two sets of cities. Presumably a city that is likely to gain substantially from Amazon locating with it (e.g., a greater need to increase jobs) is more likely to attract Amazon with greater incentive packages. By doing so, we try to overcome the inherent disadvantages of using an experiment with an endogenous location choice.

A potential concern of our Amazon setting is that government subsidies and incentives tied to Amazon's entry may indirectly influence incumbent firms' financial policies.[9] For example, Amazon's expansion could create high-demand jobs, attract skilled professionals, raise local wages, and shift employment composition. Additionally, Amazon's HQ2 could draw new firms to the area, such as startups seeking funding or acquisition, and enhance innovation among existing firms through knowledge spillovers (Jin (2019), Xue (2022)). Our difference-in-difference estimates remain robust after accounting for local labor market shifts and economic changes associated with Amazon's entry.

Our paper contributes to three major strands of literature. First, our study adds to the extensive research that intends to understand the determinants of capital structure. While early studies emphasize some specific firm attributes (e.g., Titman (1984), Titman and Wessels (1988), Rajan and Zingales (1995), Lemmon, Roberts, and Zender (2008)), recent work highlights labor market frictions, such as unemployment risk (Agrawal and Matsa (2013)), firing costs (Serfling (2016), Simintzi et al. (2015)), and unionization (Atanassov and Kim (2009), Schmalz (2016)). Our study examines whether labor market power shapes firms' financial policies. Our findings suggest that labor market power allows firms to use higher financial leverage.

Second, we contribute to the literature on 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

[9] Amazon received significant subsidies and incentives to establish its second headquarters, HQ2, in Crystal City, Arlington, Virginia. These include a direct cash grant of $23 million from Arlington County over 15 years and $195 million for transportation projects to improve mobility in Northern Virginia. Further, local investments include over $570 million from Arlington and Alexandria for additional transportation infrastructure, such as rail connections and transit facilities. See https://www.virginiabusiness.com/article/northern-virginia-lands-a-big-chunk-of-amazons-second-corporate-headquarter/.

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. We extend this line of studies by showing that firms with greater labor market power also increase financial leverage, as workers can hardly bargain with monopolistic local employers due to restricted job opportunities and high unemployment costs.

Finally, our study contributes to the labor economics literature on monopsony power. Prior research shows that increased labor market power compresses wages (Azar et al. (2020), Benmelech et al. (2020), Qiu and Sojourner (2023), Webber (2015), Rinz (2018), Yeh et al. (2022), Prager and Schmitt (2021), Arnold (2020)), increases wage inequality (Webber (2015), Rinz (2018)), and affects labor demand for different labor skills (Deming and Kahn (2018), Hershbein and Kahn (2018), Deming and Noray (2020)). We extend this literature by constructing a novel firm-level labor market power measure using online job postings and examining its impact on firms' financial policies.

II. Data and Variables

A. Data

We obtain data from two primary sources. 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 negative or missing. We obtain information on online job postings by U.S. firms in 2007 and continuously from 2010 to 2021 from Lightcast. Lightcast uses artificial intelligence to collect over 3 million job postings daily from over 50,000 job boards and corporate sites. Importantly, Lightcast 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]

Lightcast provides coverage of over 800 6-digit SOC occupations. This coverage is as comprehensive as the Occupational Employment Statistics (Hershbein and Kahn (2018)). This broad occupation coverage is compared favorably to databases that use 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 Lightcast database offers detailed information on each job posting, such as the name of the employer, occupation, industry, location (i.e., commuting zone), as well as education, certification, and categories of skill requirements. The detailed geographic information and the skill categories allow for a highly granular definition of the labor market and a large sample of firm-level analysis.

To construct our firm-level labor market power measure, we conduct a two-step matching of firm names between Compustat and Lightcast. Given our focus on a firm-level analysis, we restrict our Lightcast sample to job postings with non-missing employer names that posted at least three job postings in a given labor market.[11] We start by using fuzzy name-matching techniques to match the employer names from Lightcast and firm names from Compustat. This process involves the matches between multiple employer names stated in slightly different formats and one Compustat firm name.[12] Then, we manually clean the name-matching pairs to

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[10] Lightcast 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 Lightcast database. Also, Lightcast cleans the duplicated listings if it collects the same job posts from various platforms.

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

[12] For example, employer names "Air products chemical inc," "Air products & chemicals," and "Air products chemicals" are all matched to "Air Products & Chemicals."

ensure the quality of these matches. Our final sample consists of 15,294 firm-year observations that cover 2,645 unique Compustat firms.

B. Labor market power (LMP)

A key distinction between our approach and earlier studies is that we construct a firm-level metric of labor market power. Prior studies measure monopsony using the Herfindahl-Hirschman Index (HHI) of employment concentration in a given local labor market. For example, Rinz (2018) and Lipsius (2018) use the Census Longitudinal Business Database (LBD) data to calculate labor market concentration by commuting zone and four-digit NAICS industry. Benmelech et al. (2020) use the plant-level U.S. Census Bureau's LBD data to measure the labor market concentration at the county and industry level. To better capture the labor market power at the occupational level, Qiu and Sojourner (2023) estimate the occupational distribution of employment within each industry and impute employment by occupation for each establishment. Azar, Marinescu and Steinbaum (2020) use CareerBuilder.com job postings across seventeen occupations to measure labor market concentration by commuting zone and occupation. Azar, Marinescu, Steinbaum, and Taska (2020) further develop a more comprehensive measure of labor market concentration at the occupation-commuting zone level using Lightcast job postings.

An HHI-based labor market concentration measure reflects the monopsony power of an overall market. However, it cannot capture a firm's relative importance in its respective labor market, thus masking heterogeneity in the labor market power across firms within a labor market. To overcome such limitations and provide a more accurate assessment of firm-level labor market power, we propose a direct measure of firm-specific monopsony power using a firm's labor market share. This measure evaluates the extent to which an individual firm controls employment within a given labor market.[13]

Specifically, to measure a firm i's labor market power, 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:

(1a) $$V_{m,t} = \sum_i V_{i,m,t}$$

(1b) $$V_{i,t} = \sum_m V_{i,m,t}$$

where $V_{i,m,t}$ is the number of firm i's job posts in the local labor market m in year t. We include all the firms that post valid jobs in Lightcast in our sample, irrespective of whether the firms can be matched to Compustat files. Then we calculate the fraction of firm i's job posts in the local labor market m in year t,

(1c) $$S_{i,m,t} = V_{i,m,t}/V_{m,t}.$$

Intuitively, $S_{i,m,t}$ measures firm i's power (or market share) in market m. A high (low) value of $S_{i,m,t}$ suggests that firms operating in the local labor market m have large (limited) market power when recruiting employees from the local market m.

To measure the firm's overall labor market power across the various (local) labor markets and skill clusters in which it hires, we calculate our key empirical measure of firm-level labor market power (LMP) as:

(2) $$LMP_{i,t} = \sum_m \frac{V_{i,m,t}}{V_{i,t}} \times S_{i,m,t}.$$

[13] We greatly appreciate an anonymous reviewer for this insightful comment. Our results are robust to an HHI-based labor market power measure.

where $\frac{V_{i,m,t}}{V_{i,t}}$ is the share of firm i's hiring in a given local labor market m, which captures the relative importance of market m to its entire hiring effort.

A higher level of LMP indicates that firm i is a relatively more powerful employer in the labor market after accounting for its importance (relative to competing employers) across various geographic locations and skill clusters.

As a robustness check, we also construct another measure of a firm's labor market power at the commuting zone (CZ) level:

(3) $$LMP(CZ)_{i,t} = \sum_{CZ} \frac{V_{i,CZ,t}}{V_{i,t}} \times S_{i,CZ,t}.$$

where $S_{i,CZ,t} = V_{i,CZ,t}/V_{CZ,t}$ measures firm i's power (or market share) in the commuting zone (CZ), $\frac{V_{i,CZ,t}}{V_{i,t}}$ is the share of firm i's hiring in a given commuting zone CZ.

C. Other firm-level variables

We construct four measures of financial leverage. Book leverage is calculated as the book value of long-term debt plus debt in current liabilities divided by the book value of assets. Market leverage is calculated as the book value of long-term debt plus debt in current liabilities divided by the market value of debt and equity (long-term debt plus debt in current liabilities plus market value of equity). We also consider two alternative net leverage ratios.[14] 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.

[14] 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)).

We include a set of firm-level control variables related 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 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 indicates 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 the effect of pledgeable collateral assets on a firm's borrowing capacity. A modified Altman z-score (AZ) (MacKie-Mason (1990)) captures a firm's financial strength and bankruptcy likelihood. The extended labor share (ELS), which captures the labor intensity of a firm's operation, is computed as the imputed labor expenses divided by the value-added of a firm as in Donangelo et al. (2019).

Table 1 presents summary statistics for our key variables, including the mean, median, 25th and 75th percentiles, and standard deviation. Using our baseline labor market definition at 6-digit SOC and commuting zone, the average LMP is 0.087, with a standard deviation of 0.148. On average, firms recruit from 18 commuting zones and 468 local labor markets defined by commuting zone and 6-digit SOC. This suggests that firms generally operate in relatively competitive labor markets. 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 29% (22%). An average firm holds 1,026 million total assets and has a market-to-book ratio of 2.6. On average, dividends are paid in 38% of firm-year observations. The average ROA and tangibility are -0.02 and 0.50, respectively. On average, a firm has a modified Altman z-score of -0.72 and an extended labor share of 0.56.

[Insert Table 1]

In the Internet Appendix, Figure IA.1, we sort sample firms into quintiles yearly based on our baseline local labor market power measure and plot the average leverage ratios by quintile. The average book leverage (market leverage) rises from 25.6% (15.8%) in the bottom LMP quintile to 31.9% (29.8%) in the top LMP quintile. The difference in average book leverage (market leverage) between the top and bottom HHI quintiles is 6.3% (14%) and is highly significant. This univariate analysis provides preliminary evidence of a positive relationship between a firm's labor market power and financial leverage ratios.

III. Empirical Results

A. Baseline results

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

$$LEV_{i,t} = \beta LMP_{i,t-1} + \gamma' X_{i,t-1} + \alpha_i + \tau_t + \varphi_{cz} + \varepsilon_{i,t}, \tag{4}$$

where i and t denote firm and year, respectively. The dependent variable, LEV, 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. LMP is the firm-level labor market power measure in equation (2). The main coefficient of interest is β, which measures the correlation between a firm's labor market power and its financial 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.

Unobserved local economic factors or industry structures may influence both labor market power and firms' debt usage. For example, high-tech firms competing for engineers in San Francisco-San Mateo-Redwood (CZ 294) face different labor market dynamics than those in Minneapolis-St. Paul-Bloomington (CZ 47) and typically have lower financial leverage. To address this issue, we include a local market fixed effect (φ_{cz}) in our specification. We define the local market as the commuting zone (CZ) of the firm's headquarters, which is assumed to be the major market where the firm hires. Standard errors are clustered at the commuting zone level.

[Insert Table 2]

Columns 1 – 4 of Table 2 present the baseline results on the relationship between a firm's labor market power and its financial leverage. We find consistently positive and statistically significant coefficients on LMP across all four leverage measures, ranging from 0.051 to 0.085. Economically, a one standard deviation increase in labor market power correlates with a 0.94% (0.75%) rise in book (market) leverage, representing a 3.2% (3.4%) increase relative to the sample means. The economic significance is even more prominent for net book and net market leverage: an increase in one standard deviation of LMP is correlated with a 1.3% (1.2%) increase in net book leverage (market leverage). These findings are consistent with our hypothesis that the labor market power of employers restricts workers' outside options and leads firms to adopt a more aggressive capital structure.

Unobserved industry-level time-varying factors may influence both a firm's capital structure and its exposure to local labor market conditions. Prior research (e.g., MacKay and Phillips 2005) finds 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 this, we incorporate local labor market fixed effects and industry × year fixed effects in equation (4) to control for time-varying industry dynamics. Columns 5 – 8 of Table 2 show that the positive relationship between labor market power and firm leverage remains statistically significant and economically strong even under this stricter specification.

As a robustness check, we re-estimate our specifications using the alternative labor market power defined at the commuting zone level (as in equation (3)). The results are presented in the Internet Appendix, Table IA.1, columns 1 – 4. We follow the same specification as in Table 2 and find that the documented positive relation between a firm's labor market power and financial leverage remains intact using an alternative definition of the labor market: the coefficients for LMP(CZ) are positive and highly significant.

A potential concern of our baseline finding is 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). To test for robustness, in Table IA.2 in the Internet Appendix, we provide the results of re-estimating equation (4), excluding 2007. The results remain unchanged, confirming the stability of our findings.

B. Controlling for endogenous hiring weight

A potential concern in our baseline analysis is the endogeneity of time-varying weights assigned to different hiring markets. Our proxy for a firm's exposure to labor market power aggregates local markets using weights that may reflect where the firm intends to grow rather than the firm's current workforce composition. Furthermore, the differential weights assigned to a firm's hiring markets based on its job posts may introduce reverse causality—firms in financial distress may shift hiring toward labor markets where they have more power and away from labor markets where they have limited power. Consequently, time-varying market weights could create a spurious correlation between LMP and financial leverage.

To address this issue, we consider two alternative measures for a firm's labor market power. The first measure is a fixed weighted labor market power measure where the firm's hiring weight in a given labor market m is fixed at an early stage of the sample period – i.e., only the labor market shares have variation over time:

(5a) $$LMP_{i,t}(FIX) = \sum_m \frac{V_{i,m,t_0}}{V_{i,t_0}} \times S_{i,m,t}.$$

where $\frac{V_{i,m,t_0}}{V_{i,t_0}}$ is the share of firm i's hiring in a given local labor market m at the beginning of the sample period or the first year when the firm starts hiring in the local labor market m.

The second measure is an employment-share-weighted sum of the labor market shares across a firm's hiring labor markets. To compute the employment share at a given local labor market m, we aggregate the firm-level employment across different local labor markets from the individual-level workforce data from Revelio Labs.[15]

We match approximately 60% of our sample firms with those covered by individual-level workforce data from Revelio Labs. For each firm in the overlapped sample, we compute the employment share as the aggregated number of employees divided by the total employees in each local labor market. The employment share weighted labor market power is defined as:

(5b) $$LMP_{i,t}(EMP\ SHR) = \sum_m EMPSHR_{i,m,t} \times S_{i,m,t} = \sum_m \frac{Emp_{i,m,t}}{Emp_{i,t}} \times S_{i,m,t}.$$

[15] Revelio Labs consistently collects unstructured data, including online profiles and resumes of employees, from diverse websites and social media platforms like LinkedIn. They assimilate and standardize vast amounts of public employment records, forming one of the world's initial universal HR databases. The raw data comprises over 380 million online public profiles and resumes of employees affiliated with over 5,000 public companies. See https://www.data-dictionary.reveliolabs.com/data.html#individual-level-data.

If the positive relation we documented between LMP and financial leverage were due to a mechanical relation between a firm's choice of hiring markets (not its market power) and its financial condition, then we should not observe any significant relation between the two alternative measures.

[Insert Table 3]

The results, reported in columns 1 – 4 of Table 3, show that the coefficients associated with fixed-weighted labor market power are consistently positive and statistically significant. Similarly, albeit with a smaller sample, the coefficients for the employment share weighted labor market power measure reported in columns 5 – 8 of Table 3 are also consistently positive and significant. These results suggest our baseline results are not driven by the correlation between the weights assigned to hiring markets and the firm's financial condition.

C. Labor market power vs. product market power

A key challenge in our analysis is disentangling the effects of labor market power from product market power, given that firms within the same industry often compete for talent in overlapping labor markets. For example, high-tech firms like Apple and Microsoft compete not only for specialized talents –i.e., computer engineers – but also for the similar products they offer – i.e., cloud computing. While industry-times-year fixed effects help control for broad industry-wide time-varying shocks, they may not fully capture the dynamics of product market competition given that the SIC codes do not accurately describe a firm's product spaces (Hoberg and Gordon (2015, 2010)).[16]

[16] The Text-based Network Industry Classification (TNIC) is built using pairwise similarity scores derived from the textual analysis of firms' 10-K product descriptions. In contrast, the Standard Industrial Classification (SIC) system employs a categorical framework, grouping firms into predefined industries based on broad sectoral definitions.

To address this concern, we implement two approaches. First, we construct an alternative labor market power measure using only the job posting of firms in a given labor market that do not compete with a focal firm in the same product space. We follow Hoberg and Phillips' (2010, 2015) 10-K Text-based Network Industry Classifications (TNIC) to group firms into product market spaces each year based on the similarity of their product offering using the textual analysis of firm's 10-K product description.[17] We then reconstruct the market share of firm i in a given labor market using only the job posts from firms who do not compete with firm i in the same TNIC product market space, $S_{i,m,t}^{Excl.TNIC} = V_{i,m,t}/V_{m,t}^{Excl.TNIC}$. The labor market power is thus defined as :

(6) $$LMP(EXCL.TNIC)_{i,t} = \sum_m \frac{V_{i,m,t}}{V_{i,t}} \times S_{i,m,t}^{Excl.TNIC}$$

This approach effectively isolates labor market power by ensuring that product market interactions do not influence the measure. The results are reported in columns 1 – 4 of Table 4. The coefficients for LMP(EXCL. TNIC) are all positive and statistically significant, irrespective of leverage ratio considered.

The second approach we use to address the concern is that we use the original LMP measure but explicitly control for product market effects by incorporating TNIC Community × Year fixed effects, which account for time-varying competition dynamics within (precisely defined) product market spaces.[18] Columns 5 – 8 of Table 4 report the results. We observe that the positive relationship between labor market power and financial leverage remains robust.

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[17] See https://hobergphillips.tuck.dartmouth.edu/tnic_basedata.html.

[18] We develop a categorical industry classification based on firm pairwise similarity scores provided by Hoberg and Phillips (2010, 2015). Specifically, we represent annual TNIC firm pairs as a unidirectional weighted network, where firms serve as nodes, and edges—along with their associated weights—capture the similarity scores, reflecting the strength of product market connections. We then apply the Louvain method for community detection to identify non-overlapping firm communities within this network. Each community, analogous to an industry, consists of firms with more similar product descriptions to each other than to firms outside the group. This approach enables a dynamic categorical industry classification that directly derived from TNIC pairwise relationships.

Taken together, both approaches yield consistent results, confirming that our findings on labor market power are not driven by product market dynamics.

[Insert Table 4]

D. Controlling local labor market dynamics

Another concern is that our measure of local labor market power may be correlated with broader local economic or labor market conditions. Kim (2020) finds that firms increase debt usage as local labor markets expand, as larger markets enhance job search efficiency and reduce unemployment costs. Similarly, factors such as household income, unemployment rates, and workforce composition may also correlate with labor market power. To account for this concern, we specifically control for several time-varying local economic and labor market characteristics, including annual percentage changes in the local labor force (proxying labor market size), unemployment rates, the fraction of the workforce with a bachelor’s degree or higher, and the logarithm of median household income at the county level.[19]

Table 5, Panel A reports the results that include the local economic and labor market characteristics. Even after accounting for key local labor market characteristics, the coefficients for a firm’s labor market power remain positive and statistically significant. Our findings indicate that labor market power is a unique feature of the firm, distinct from labor market size and other correlated economic and labor market factors that the firm faces.

We further address the concern that the unobserved local economic and labor market conditions may correlate with our measure of local labor market concentration and drive the

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[19] The labor force and unemployment rate at county-level are obtained from Local Area Unemployment Statistics of BLS (https://www.bls.gov/lau/tables.htm). The percentage of educated population and household income are obtained from the Current Population Survey (CPS) from U.S. Census Bureau (https://www.census.gov/programs-surveys/cps/data/datasets.html).

increase in leverage. For example, the time-varying economic shocks to different hiring markets may correlate with the changes in labor market power and the firm's financial policy.[20] A way to control for such an effect would be to include all the hiring markets-times-year fixed effects. This approach is empirically infeasible as an average firm hires from 18 commuting zones and 468 local labor markets defined by commuting zone and 6-digit SOC. Instead, we implement a more practical solution – e.g., controlling for time-varying economic conditions at the headquarters' commuting zone level by including Commuting Zone × Year fixed effects.[21]

Table 5, Panel B presents the results, showing that the positive and significant coefficients for LMP remain robust. This indicates that at least time-varying economic shocks to a firm's largest hiring market do not drive the positive relationship between labor market power and financial leverage. We further address endogeneity concerns in Section 4.

[Insert Table 5]

E. Cross-sectional analysis

We now examine how the relationship between labor market power and financial leverage varies by the types of talent firms hire. Schubert et al. (2024) highlight significant heterogeneity in labor market power across occupations and regions. Workers in different occupations and regions have access to substantially different outside options. We rely on such literature and test how the positive correlation between labor market power and leverage varies across several occupation characteristics indicative of employees with disparate external options.

1. Occupation mobility

[20] For example, a persistent and positive economic shock may allow firms to hire more aggressively and have lower labor market power while it also boosts firms' cash balance and lower their financial leverage.
[21] Approximately 80% of the firms' largest hiring market is the commuting zone of its headquarters.

Our first measure of employee outside options is based on occupational mobility, which varies significantly across occupations and times (Kambourov and Manovskii (2005, 2008, 2009a), Alvarez and Shimer (2009)). For example, Kambourov and Manovskii (2005, 2008) document a considerable increase in workers switching occupations over time, and occupational mobility is intimately related to wage inequality. The external options of workers are contingent upon their ability to swiftly switch jobs, thereby mitigating any associated costs of job loss. We hypothesize that the extent to which the labor market power of employers restricts employee outside options varies by the type of occupations that firms hire.

Following Kambourov and Manovskii (2008), we define occupational mobility as the fraction of currently employed individuals in each occupation who report a different occupation from their previous report. We use data from the Survey of Income and Program Participation (SIPP), a longitudinal U.S. Census Bureau survey that provides comprehensive information on household income and employment status.[22] We first define high-mobility occupations as those with occupational mobility above the annual median. We then calculate the percentage of a firm's Lightcast job postings targeting high-mobility occupations each year. Finally, we define HIGH_LABOR_MOBILITY as a dummy variable equal to 1 if a firm's percentage of job postings for high-mobility occupations is above the location median and zero otherwise.

Columns 1 – 4 of Table 6 show that the interaction terms between LMP and HIGH_LABOR_MOBILITY are negative and statistically significant across all leverage measures. These findings support our hypothesis that the impact of labor market power on financial leverage is mitigated for firms employing workers in high-mobility occupations.

[Insert Table 6]

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[22] We obtain SIPP data from the U.S. Census Bureau: https://www.census.gov/programs-surveys/sipp.html.

2. Skill similarity

Our second measure of employee external options is the similarity in skills required between job posts targeted by the focal firm and those pursued by the other firms within the same geographical location. High skill similarity indicates a labor market where workers have greater external opportunities and can easily transition between jobs. Prior research highlights that certain skills are not easily transferable across occupations or employers (Lazear (2009)). Tate and Yang (2024) show that firms benefit from internal labor markets when operating across industries with overlapping skill demands, which facilitates human capital reallocation and skill transferability. We hypothesize that if the labor market power of employers restricts workers' outside options and drives a higher use of debts, this effect should be weaker for firms hiring workers with high skill similarity to those sought by other local employers.

Specifically, we measure the similarity in skills required between job posts targeted by the focal firm and those pursued by the other firms within the same geographical location using the cosine similarity approach.[23] First, we calculate the number of skills required by a focal firm (vector $X_{i,t-1}$) and the number of skills required by the other firms (vector $Y_{-i,t-1}$)) in the same commuting zones within each skill cluster defined by Lightcast.[24] Next, we use the cosine measure as a similarity function,

(7) $$SKILL\ SIMILARITY\ (X_{i,t-1}, Y_{-i,t-1}) = \frac{X_{i,t-1} \cdot Y_{i,t-1}}{\|X_{i,t-1}\| \|Y_{-i,t-1}\|}$$

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[23] Cosine similarity measures the similarity between two vectors of an inner space. It measures the angle between two vectors and examines whether two vectors point to the same direction. It is often used to measure similarly in textual analysis (Han, Kamber, and Pei 2012).

[24] Lightcast contain a total of 31 skill categories and more than 350 skill clusters. See their classification of skill clusters: https://lightcast.io/open-skills/categories.

where $\|X_{i,t-1}\|$ is the Euclidean norm of vector $X = (x1_{i,t-1}, x2_{i,t-1}, \ldots, xP_{i,t-1})$, defined as $\sqrt{x1_{i,t-1}^2 + x2_{i,t-1}^2 + \cdots + xP_{i,t-1}^2}$. Similarly, where $\|Y_{-i,t-1}\|$ is the Euclidean norm of vector $Y_{i,t-1}$. The skill similarity computes the cosine of the angle between the two vectors, which captures how closely the skills hired by the focal firms are relative to those hired by the other firms in the same location. Lastly, HIGH_SKILL_SIMILARITY is a dummy taking a value of 1 for firms with the skill similarity above the location median and zero otherwise.

The results are reported in columns 5 – 8 of Table 6. Again, we see that the coefficients for the interaction terms are negative and statistically significant, irrespective of the financial leverage considered. This suggests that the impact of labor market power on firms' debt usage is weaker for firms employing workers with high skill transferability. Together, these cross-sectional analyses support our hypothesis that firms' ability to increase financial leverage using labor market power is constrained when their workers have greater external options.

F. Tax shield or labor rigidity reduction

As previously discussed, local labor market power can affect corporate leverage through two channels: higher profits and debt capacity via the tax shield or reduced labor rigidity. We now empirically test which mechanism drives this relationship.

The first channel follows the standard trade-off theory: labor market power enables firms to suppress wages and enjoy higher profits, which strengthens the firm's incentive to borrow to get tax shields. However, lower wages and higher profits could also reduce financing needs or alter firms' optimal capital-labor ratios.[25] To test this, we examine whether firms with greater

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[25] For example, some prior studies (e.g., Graham (2000), Hennessy and Whited (2005)) do not find strong support for the impact of profitability and tax benefits on financial leverage.

labor market power experience higher profitability. Panel A of Table 7 presents the results, showing that the coefficients for labor market power are largely insignificant across specifications. This suggests that the tax shield benefits from higher profits do not provide a viable channel through which labor market power affects the firms' incentive to borrow.

[Insert Table 7]

We now test the second channel, which suggests that firms increase financial leverage because labor market power allows firms to enjoy greater flexibility in adjusting labor costs. If reduced labor rigidity allows firms to manage employment more flexibly, we expect to observe (i) lower earnings volatility for firms with greater labor market power and (ii) a higher likelihood of downsizing employment following negative cash flow shocks. Panel B of Table 7 reports the regression results of earnings volatility on a firm's labor market power. Earnings volatility is measured as the standard deviation of income before extraordinary items plus depreciation and amortization, scaled by book assets over the past five years. The coefficients for labor market power are consistently negative and statistically significant across specifications. This finding supports our second channel that firms with higher labor market power experience lower earnings volatility due to reduced labor rigidity.

As an additional test, Panel C of Table 7 examines how firms adjust employment in response to profit declines, conditional on their labor market power. Following Serfling (2016), we measure employment changes as the one-year percentage change in a firm's number of employees. Profit declines are captured by a dummy variable equal to 1 if profitability (i.e., defined as income before extraordinary items plus depreciation and amortization scaled by book assets) is negative in a given year. The negative coefficients on the profit decline suggest that firms downsize employment following declines in profitability. More importantly, the interaction term between LMP and profitability decline is also negative and statistically significant across all specifications. This indicates that labor market power enables firms to adjust employment flexibly during downturns. These results reinforce the flexibility channel as the primary mechanism through which labor market power influences firms' capital structure decisions.

IV. The Experiment: Amazon's HQ2 establishment

We now further address the remaining endogeneity concerns using a unique quasi-natural experiment: the establishment of Amazon's second headquarter (HQ2) in Crystal City.

A. Amazon HQ2: empirical set-up

The positive relationship between labor market power and financial leverage may be endogenous, as unobserved factors could influence both the labor market power and a firm's use of financial leverage.[26] To mitigate this concern and strengthen causal inference, we exploit the establishment of Amazon HQ2 in Crystal City, Arlington, Virginia, as a quasi-natural experiment. This well-documented event, with clearly defined timelines, provides an exogenous shock to the labor market power of incumbent firms. Amazon's entry reduces labor market power by expanding workers' external options and lowering unemployment costs. As a result, incumbent firms facing greater competition for talent acquisition would respond by decreasing financial leverage. This setting allows us to assess how changes in labor market power influence firms' capital structure decisions.

[26] 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 reduced labor market power of incumbent firms. 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 power 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, the issue of endogeneity remains exist.

Amazon announced its HQ2 expansion in September 2017, planning a $5 billion investment and up to 50,000 new jobs upon completion of its HQ2. After evaluating proposals from over 200 cities across North America that offered a combination of tax breaks, expedited construction approvals, etc., the company released a shortlist of 20 finalists on January 19, 2018. 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,[27] making Northern Virginia the sole HQ2 site.[28] Amazon's aggressive hiring in Northern Virginia created an exogenous shock to the labor market power of the incumbent firms, as incumbent firms faced intensified competition for workers.[29] Therefore, we use Amazon's HQ2 expansion as our primary empirical setting to establish causality.

The Amazon HQ2 expansion serves as an ideal empirical setting for several reasons. First, the skill categories that Amazon hires are well-defined, allowing us to clearly identify incumbent firms competing for the same talent as Amazon. Second, the shock to local labor market power was largely unanticipated. There was no clear frontrunner before the final announcement, and Amazon was still negotiating with multiple cities just days before the final announcement. This makes it unlikely that local firms adjusted financial leverage in anticipation

[27] 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.

[28] 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.

[29] 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

of any direct effects or externalities associated with Amazon's entry.[30] Third, any positive externalities from Amazon's entry would bias us against finding a negative impact on incumbent firms' leverage. For instance, Amazon's entry into Crystal City attracts people to move into the region, leading to an appreciation of local residential and commercial real estates. 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 (e.g., Titman and Wessels (1988), Cvijanović (2014), Rampini and Viswanathan (2013)). Finally, and most importantly, Amazon's entry affects the labor market but not product market competition due to its internet-sales model. This ensures our analysis isolates the labor market effect without confounding factors from product market dynamics.

A key empirical challenge is that Amazon's HQ2 location was not randomly assigned. Firms select locations based on expected profitability, which depends on location-specific factors such as infrastructure, skilled labor supply, and local regulatory environment (Greenstone and Moretti (2004)). As Glaeser (2001) highlights, locations with strategic advantages or specific natural resources that align with the needs of certain types of firms tend to attract repeated investments from such firms, making it difficult to fully disentangle the effects of Amazon's entry from preexisting local market characteristics.

Following Greenstone, Hornbeck, and Moretti (2010), we define firms in Crystal City and adjacent commuting zones, the "winner" city, as treated firms and firms in New York City—Amazon's closely run-up bidder that was initially selected but later withdrawn—as the counterfactual. Since firms located in the "winner" city and closely run-up bidding city are both

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

perceived as close “good match” to Amazon’s needs for its HQ2, this set-up mitigates the concern of an endogenous location choice associated with specific local characteristics.

A potential concern is that although Amazon HQ2 was announced in 2018, construction began in 2020 and was completed in 2023. To confirm that Amazon’s announcement of HQ2 immediately impacted the labor market, we analyze its job postings in Crystal City and adjacent commuting zones around the announcement. Figure IA.2 shows the number of job postings in Amazon’s top five hiring occupation categories before and after the announcement of HQ2.[31] By 2019, just a year after the announcement, Amazon had 4,204 job postings in CZ74 and adjacent commuting zones, with over one-third in its top five hiring occupation categories. Notably, job postings for software developers (SOC 15-1132) doubled pre-announcement levels in 2019 and 2020 and surpassed four times pre-announcement levels by 2021. These patterns confirm that Amazon’s HQ2 announcement immediately affected local labor market dynamics.

B. Amazon HQ2: Difference-in-difference (DiD) Analysis

1. Main analysis

We use a difference-in-differences approach to examine how treated and control firms adjust their capital structure after the announcement of Amazon’s entry. Following Greenstone, Hornbeck, and Moretti (2010), we define the firms located in commuting zone 74 and its adjacent commuting zones as treated firms – i.e., firms in “winner” city, and we define the firms located in New York City as control firms – i.e., firms in closely run-up “losing” city. We do not compare the winning city to all other U.S. cities due to unobserved heterogeneity between the two groups, as cities expected to gain more from Amazon’s entry (e.g., a greater need to boost

[31] The top five SOCs that Amazon’s Seattle HQ hires are Software Developers, Marketing Managers, General Managers, Computer Occupations, and Operational Managers, which constitute about 50% of hiring by Amazon.

local employment) are likely to offer stronger incentive packages. By doing so, we overcome the inherent disadvantages of using an experiment with an endogenous location choice. To identify firms' historical headquarters, we use Augmented 10-X Header Data from the University of Notre Dame, which compiles firms' historical headquarters using information from 10-K/Q filings on EDGAR.[32]

We focus on treated firms with job posts during the pre-event period that overlapped with Amazon's top hiring occupation categories, as these firms demand the labor force of similar skill categories as Amazon and thus experience the most significant decline in their labor market power following Amazon's entry. Leveraging the granularity of Lightcast data, our definition of treated and control firms transcends industry boundaries, recognizing that firms within the same industry may require vastly different skill sets. Restricting the analysis to treated and control firms hiring from the same skill categories as Amazon mitigates concerns that differences in financial leverage adjustments between treated and control firms are driven by the differential skill categories hired by treated and control firms.

To identify Amazon HQ2's top hiring skill categories, we analyze its 2014–2017 hiring patterns at its Seattle HQ location (CZ 171). Panel A of Table 8 shows that Amazon's top five hired occupations were Software Developers, Marketing Managers, General Managers, Computer Occupations, and Operational Managers, with the occupation of Software Developers accounting for 22.7% of all Amazon's job vacancies. Since HQ2 serves a similar function, we assume hiring patterns in CZ 74 will be comparable. [33] For each incumbent firm in both "winning" and "losing" cities, we identify skill categories in which they posted job ads during

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[32] https://sraf.nd.edu/data/augmented-10-x-header-data/.

[33] 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.

the pre-event period of 2014–2017 and restrict our analysis to treated and control firms that overlap with Amazon's top hiring categories. This yields a final sample of 43 treated firms and 31 control firms with available data on labor market power (LMP), control variables, zip codes, and industry codes.

To capture the granular effect of this event on treated firms' financial leverage, we use a four-year window before and a three-year window after the announcement of HQ2 in 2018. Specifically, we estimate the following difference-in-difference regression:

$$LEV_{i,t} = \beta TREAT_i \times POST_t + \gamma' Z_{i,t-1} + \alpha_i + \tau_t + \varphi_{cz} + \theta_{jt} + \varepsilon_{i,t}, \tag{8a}$$

TREAT is an indicator variable that is set to one from 2019 to 2021 and zero for the pre-treatment period from 2014 to 2017. θ_{jt} is industry-times-year fixed effect, which captures the time-varying industry shock. We exclude the announcement year of 2018 to avoid any confounding effect during the event year. The vector $Z_{i,t-1}$ include all the control variables as in equation (4) and their corresponding interaction terms with POST dummy. The parameter of interest is β, which measures the differential change in leverage after the shock between the treated group and the control group. Similar to our main analysis, we also include firm, year, firm headquarters' commuting zone, and industry-times-year fixed effects in the specification. Because of this, the main terms TREAT and POST are subsumed by the fixed effects.

Table 8, Panel B presents the results, showing a negative and statistically significant coefficient on TREAT × POST across all leverage measures. For example, the coefficient of -0.063 in column 1 indicates that, compared to control firms, treated firms reduced their book leverage ratio by 6.34% post-shock, which is an economically sizeable effect. Importantly, we control for time-varying industry dynamics using industry-times-year fixed effects, ensuring that the results are not driven by differential time-varying industry shocks to the treated and control firms. These findings suggest that following Amazon HQ2's entry into Crystal City, treated firms adopted a more conservative financial policy than control firms.

[Insert Table 8]

[Insert Figure 1]

2. Parallel trend analysis

For difference-in-differences estimation, the parallel trend assumption must hold to ensure validity. In our context, in the absence of the Amazon HQ2 shock, the leverage ratios of the treated and control groups should have followed similar trends before Amazon's entry. To test this, we replace POST with seven time-specific indicators. The pre-announcement dummies, AMAZON_HQ2_YR(-4) (i.e., 2014), AMAZON_HQ2_YR (-3) (i.e., 2015), AMAZON_HQ2_YR (-2) (i.e., 2016), and AMAZON_HQ2_YR (-1) (i.e., 2017), equal one for four, three, two, and one year before the announcement, respectively. The post-shock dummies, AMAZON_HQ2_YR (+1) (i.e., 2019), AMAZON_HQ2_YR (+2) (i.e., 2020), and AMAZON_HQ2_YR (+3) (i.e., 2021), equal one for one, two, and three years after the shock. AMAZON_HQ2_YR (-4) is the omitted year category for the dynamic difference-in-difference estimation. We exclude 2018 to avoid confounding effects during the announcement year, as in equation (8a). We would observe pre-trends if treated firms adjusted leverage in anticipation of externalities from Amazon's entry. Specifically, significant coefficients for the interaction terms of treated dummy and pre-announcement dummies would indicate potential reverse causality. We estimate the following granular difference-in-differences regression:

(8b)

$$
\begin{aligned}
LEV_{i,t} = \theta_1[TREAT_i \times AMAZON\_HQ2\_YR(-3)] \\
&+ \theta_2[TREAT_i \times AMAZON\_HQ2\_YR(-2)] \\
&+ \theta_3[TREAT_i \times AMAZON\_HQ2\_YR(-1)] \\
&+ \theta_4[TREAT_i \times AMAZON\_HQ2\_YR(+1)] \\
&+ \theta_5[TREAT_i \times AMAZON\_HQ2\_YR(+2)] \\
&+ \theta_6[TREAT_i \times AMAZON\_HQ2\_YR(+3)] + \gamma' Z_{i,t-1} + \alpha_i + \tau_t + \varphi_{cz} \\
&+ \theta_{jt} + \varepsilon_{i,t},
\end{aligned}
$$

where all the variables are defined as in equation (8a) except for the dummy variables. As shown in Panel C of Table 8, the coefficients on the interaction terms between TREAT and pre-announcement dummies are all small and statistically insignificant, while the coefficients on TREAT × AMAZON_HQ2_YR(+2) and TREAT × AMAZON_HQ2_YR(+3) are all negative and statistically significant. To visualize the parallel trend, we also graph the time-series estimates of the above granular difference-in-difference specification as well as their corresponding confidence intervals in Figure 1. Our estimation results and the figure show that there appears to be no differential trend between treated and control firms before the announcement of Amazon's HQ2, and the impact on treated firms' financial leverage becomes evident only two years after the announcement. These findings support the quality of our difference-in-difference specifications and provide a causal interpretation of our results overall.[34]

3. Excluding product market peers

[34] While our main analysis justifies using only the closely contested runner-up city (NYC) as the counterfactual to mitigate concerns about Amazon's endogenous location choice, this approach limits the sample size. To address this, we expand the control group to include firms from all 18 shortlisted U.S. cities (including Atlanta, Austin, Boston, Chicago, Columbus, Dallas, Denver, Indianapolis, Los Angeles, Miami, Montgomery County, Nashville, Newark, New York City, Philadelphia, Pittsburgh, Raleigh, and Washington D.C) and re-estimate equation (8b). Table IA.4 show that our results remain robust using a larger control sample.

Our difference-in-differences results, like the main analyses, may be confounded by the interplay between labor market power and product market power. To isolate the effects of labor market power, we re-estimate the Amazon HQ2 tests using a sample of firms that compete with Amazon for talent but not in the product market. Specifically, we exclude the treated and control firms that belong to the same product market space as Amazon using the dynamic industry classifications derived from the similarity scores of the TNIC database. This approach ensures that the observed treatment effects are driven solely by the exogenous changes to the labor market power of incumbent firms, eliminating potential confounding effects from the product market interaction of incumbent firms with Amazon.

The results of this analysis are presented in Table IA.3. We follow the same specification as in Table 8, panel B. Overall, the coefficients on TREAT × POST remain negative and highly statistically significant regardless of the measure of financial leverage. These findings reinforce our main analysis and suggest that the differential adjustment in financial leverage of treated firms relative to control firms is more likely to be driven by the exogenous changes in labor market power brought by Amazon's entry as opposed to the changes in product market interplay between incumbent firms and Amazon.

4. A local spillover effect

A potential concern is that government subsidies and incentives provided to Amazon[35] may have a spillover effect on incumbent firms, which subsequently affect their financial policy. The presence of Amazon can create new jobs, attract skilled professionals nationwide, raise local wages, change employment composition, and stimulate economic and business start-up growth.

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[35] Amazon received substantial subsidies to establish HQ2 in Crystal City, Arlington, Virginia, including a $23 million cash grant from Arlington County over 15 years, $195 million from Virginia for transportation improvements, and over $570 million in local infrastructure investments. These incentives are contingent on Amazon creating 25,000 jobs with average salaries above $150,000 and meeting office space requirements.

For example, due to high-paying job opportunities, skilled professionals may reallocate to the Crystal City area after Amazon's HQ2 announcement. Amazon's entry is also expected to lead to an increase in employment and wages, particularly in Amazon's top hiring occupations. Furthermore, Amazon's HQ2 establishment may attract new firms into the local market, such as startups that are Amazon's potential funding or acquisition targets (Jin, 2019).[36] To address this issue, we directly control the changes in labor demand, labor supply, labor force composition, and changes in the business startups' growth and innovation activities due to Amazon's entry. We provide a detailed discussion on how we measure the additional control variables in the Internet Appendix, section II.

Table IA.5 presents our findings. The coefficients for TREAT × POST remain negative and highly significant after controlling for the changes in labor demand, labor supply, labor force composition, and overall business growth and firm innovation activities. Taken together, these results suggest that our findings are robust after accounting for the local labor market dynamics and economic perspectives brought by Amazon's entry.

5. Validation test

We assume Amazon's entry into the Crystal City area reduced incumbent firms' labor market power. To validate this assumption, we conduct two tests by analyzing (i) changes in the labor market power of treated firms relative to the control firms at the commuting zone level after Amazon's entry and (ii) changes in labor market power at the commuting zone × SOC level between treated and control firms after Amazon's entry. We restrict the construction of labor market power measures for treated firms within the treated area (i.e., CZ 74 and adjacent area) as Amazon's entry only impacts the labor market power of incumbent firms in the affected region.

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[36] Xue (2022) finds that the entry of top innovative firms positively impacts the innovation activities of incumbent firms through the knowledge spillover effects.

Specifically, we reconstruct the labor market power of treated firms (control firms) as a weighted average of market shares of treated firms in CZ 74 and adjacent areas (control firms in NYC), where market shares are either defined at the commuting zone level or at the commuting zone × SOC level. We provide a detailed discussion of the test in the Internet Appendix, section II.

The results are presented in Table IA.6. The results show that, after controlling all the correlated changes brought about by Amazon's entry, the coefficients for TREAT × POST remain highly negative and significant, irrespective of the different controls included. This implies that Amazon's entry into the Crystal City area has significantly reduced the local labor market power of incumbent firms in the treated region, as expected. The validation test further confirms the validity of our premise and supports the quality of Amazon's announcement of HQ2 establishment as a quasi-natural experiment for labor market power.

V. Conclusion

We examine how labor market power influences firms' capital structure decisions. Using online job postings of U.S. firms from Lightcast during 2007 – 2021, we find a robust and positive association between labor market power and financial leverage. This finding supports our hypothesis that labor market power allows firms to pursue a more aggressive financial policy. Our documented effect varies by how employees can explore their outside options in the labor market. Specifically, the impact of labor market power on a firm's financial leverage is less pronounced when firms hire workers in high-mobility occupations or workers with transferable skills. We further show that firms with greater labor market power experience lower earnings volatility and greater flexibility to downsize employment following negative cash flow shocks, suggesting that reduced labor rigidity is the key channel through which labor market power impacts a firm's financial leverage.

To establish causality, we exploit Amazon HQ2's announcement as an exogenous shock to the labor market power of incumbent firms. We find that treated firms reduce their leverage significantly more than control firms. Our empirical findings are robust after accounting for a set of changes in local labor market dynamics and economic perspectives brought about by Amazon's entry. This identification strategy further supports that the positive relationship between labor market power and firm leverage is likely causal.

Our findings provide some of the first large sample evidence that labor market dynamics significantly impact firms' financing decisions. Understanding how firms adjust financial policies in response to labor market conditions presents a promising avenue 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 six event period indicators, including their 90% confidence interval for the difference-in-different regressions reported in Table 8, Panel C.

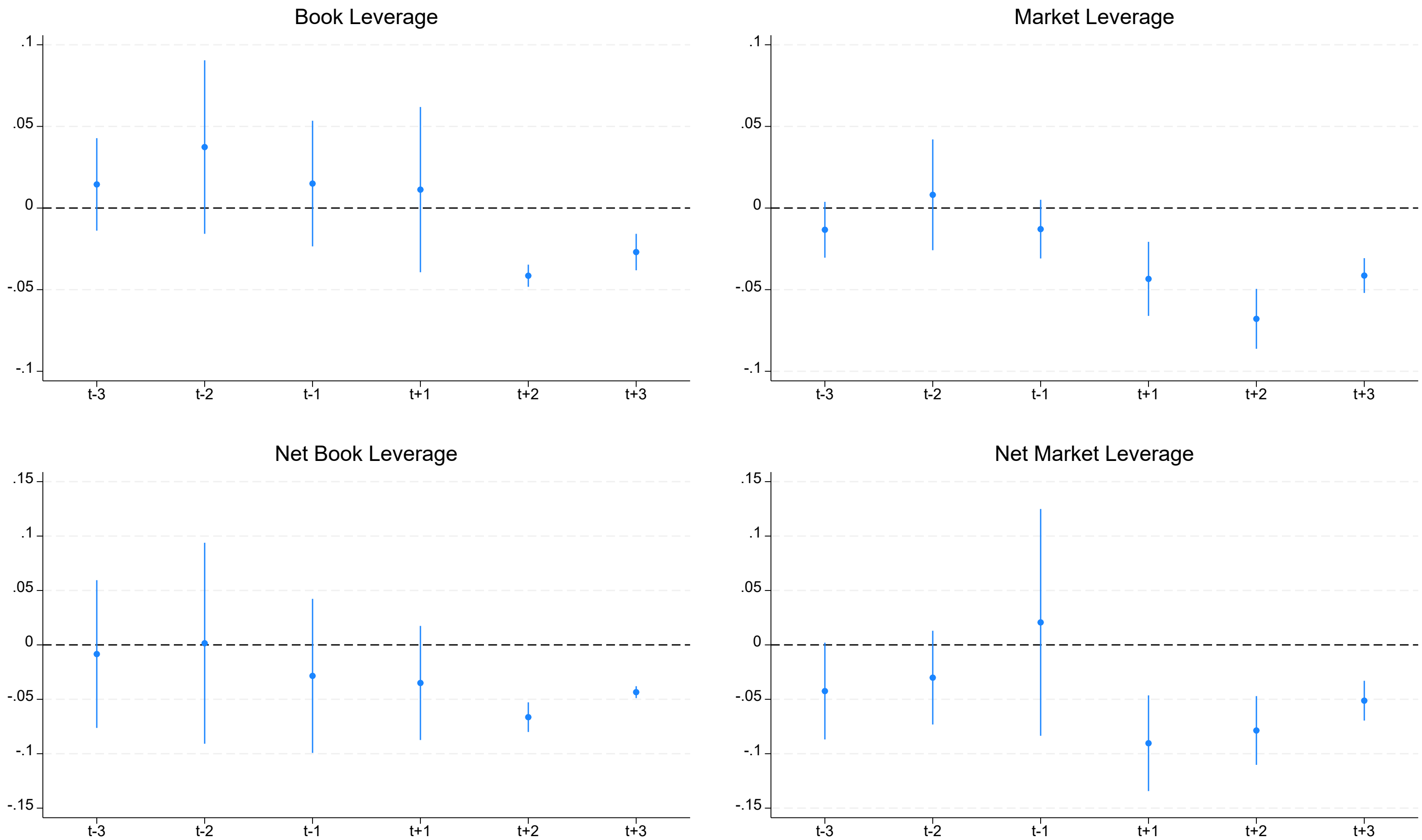


TABLE 1

Summary Statistics

This table presents the descriptive statistics of the dependent and independent variables used in the main analysis. LMP is the weighted sum of the labor market shares across all the firm's hiring markets where local labor markets are defined at the U.S. commuting zone (CZ) × occupation (6-digit SOC) level. Book leverage (BOOK) and market leverage (MKT) are computed as the ratio of long-term debt plus current liability over total assets and the ratio of long-term debt plus 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 MKT) 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 assets; 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).

	N	Mean	Std	25th	Median	75th
LMP	15294	0.0866	0.1479	0.0060	0.0269	0.1024
BOOK	15294	0.2922	0.4777	0.0637	0.2388	0.3988
MKT	15294	0.2192	0.2272	0.0283	0.1523	0.3373
NET BOOK	15294	0.0614	0.5627	-0.2084	0.0836	0.3102
NET MKT	15294	0.0760	0.3244	-0.0889	0.0510	0.2570
SIZE	15294	6.9329	2.1054	5.5187	6.9319	8.3707
M/B	15294	2.5840	4.5927	1.2466	1.7396	2.8154
ROA	15294	-0.0208	0.4733	-0.0206	0.0578	0.1073
TANGIBILITY	15294	0.4965	0.4625	0.1573	0.3398	0.7403
DIVIDEND	15294	0.3757	0.4843	0.0000	0.0000	1.0000
AZ	15294	-0.7233	21.6032	0.1797	1.2092	2.1899
ELS	15294	0.5588	1.3497	0.3400	0.6192	0.8307

TABLE 2

Baseline Results

This table presents regression results of leverage ratios on a firm's labor market power 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; specifications in columns 5 – 8 include the firm, year, local market, and industry × year fixed effects. All variables are as defined in Table 1. All independent variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	BOOK	MKT	NET	NET	BOOK	MKT	NET	NET
Independent Variables	1	2	3	4	5	6	7	8
LMP	0.0635***	0.0510***	0.0849***	0.0832***	0.0482**	0.0467***	0.0649***	0.0684***
	(3.79)	(3.16)	(3.64)	(4.08)	(2.55)	(2.73)	(2.63)	(3.22)
SIZE	0.0294***	0.0469***	0.0718***	0.0400***	0.0212**	0.0463***	0.0627***	0.0365***
	(3.01)	(7.47)	(5.55)	(3.78)	(1.99)	(8.33)	(4.30)	(3.41)
M/B	-0.0111***	-0.0046***	-0.0136***	-0.0012	-0.0123***	-0.0047***	-0.0151***	-0.0011
	(-3.85)	(-3.19)	(-4.33)	(-0.96)	(-3.40)	(-3.99)	(-3.82)	(-0.79)
ROA	-0.1586	-0.0288**	-0.1720	-0.0142	-0.1625	-0.0243**	-0.1798	-0.0181
	(-0.94)	(-2.20)	(-1.03)	(-0.66)	(-0.94)	(-2.14)	(-1.05)	(-0.81)
TANGIBILITY	0.1776***	0.1040***	0.2217***	0.1134***	0.1973***	0.0922***	0.2467***	0.1187***
	(2.82)	(7.36)	(3.61)	(5.97)	(2.83)	(6.21)	(3.68)	(6.40)
DIVIDEND	0.0196*	-0.0035	0.0275**	0.0111	0.0095	-0.0088	0.0183	0.0046
	(1.80)	(-0.58)	(2.16)	(1.04)	(0.93)	(-1.65)	(1.44)	(0.45)
AZ	0.0011	-0.0004	0.0005	-0.0002	0.0011	-0.0005	0.0007	0.0000
	(0.29)	(-0.98)	(0.15)	(-0.22)	(0.31)	(-1.41)	(0.19)	(0.01)
ELS	-0.0015	0.0013	-0.0040**	-0.0006	-0.0015	0.0012	-0.0040*	-0.0009
	(-0.81)	(1.41)	(-1.98)	(-0.57)	(-0.85)	(1.46)	(-1.96)	(-0.94)
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
Industry×Year FE					Y	Y	Y	Y
N	15294	15294	15294	15294	15294	15294	15294	15294
Adj. R2	0.835	0.809	0.851	0.788	0.841	0.835	0.857	0.805

TABLE 3

Baseline Results: Alternative Weighting Schemes

This table presents regression results of the relation between financial leverage and a firm's labor market power computed using different weighting schemes. LMP (FIX) is the weighted sum of a firm's labor market shares across all the firm's hiring labor markets using a firm's beginning-of-period hiring weight in each labor market as weights. LMP (EMP SHR) is the employment-share-weighted sum of a firm's labor market shares across all the firm's hiring labor markets. The data on firm-level employment across local labor markets is aggregated using the individual-level workforce data from Revelio Labs. All other variables are as defined in Table 1. All independent variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	BOOK	MKT	NET	NET	BOOK	MKT	NET	NET
Independent Variables	1	2	3	4	5	6	7	8
LMP (FIX)	0.0518**	0.0535**	0.0548*	0.0672**				
	(2.35)	(2.33)	(1.91)	(2.54)				
LMP (EMP SHR)					0.1815***	0.1825***	0.1833***	0.2090***
					(2.97)	(3.07)	(2.69)	(3.09)
SIZE	0.0210*	0.0461***	0.0624***	0.0362***	0.0379***	0.0435***	0.0775***	0.0451***
	(1.97)	(8.34)	(4.28)	(3.39)	(4.34)	(6.40)	(7.78)	(4.79)
M/B	-0.0123***	-0.0047***	-0.0151***	-0.0011	-0.0021	-0.0091***	-0.0059**	0.0012
	(-3.40)	(-3.99)	(-3.81)	(-0.78)	(-0.73)	(-4.43)	(-2.21)	(0.43)
ROA	-0.1624	-0.0242**	-0.1798	-0.0181	-0.1220***	-0.0432**	-0.1409***	-0.0796
	(-0.94)	(-2.14)	(-1.05)	(-0.81)	(-3.15)	(-2.12)	(-3.64)	(-0.92)
TANGIBILITY	0.1973***	0.0923***	0.2469***	0.1189***	0.1414***	0.0880***	0.1922***	0.1213***
	(2.83)	(6.20)	(3.68)	(6.42)	(4.69)	(5.42)	(5.86)	(6.96)
DIVIDEND	0.0094	-0.0089*	0.0182	0.0045	0.0217**	0.0035	0.0416***	0.0208**
	(0.92)	(-1.66)	(1.42)	(0.44)	(2.04)	(0.55)	(3.48)	(2.05)
AZ	0.0011	-0.0005	0.0007	0.0000	0.0012	-0.0003	0.0007	0.0012
	(0.31)	(-1.40)	(0.19)	(0.01)	(0.56)	(-0.23)	(0.21)	(0.27)
ELS	-0.0015	0.0012	-0.0039*	-0.0008	0.0012	0.0021**	0.0004	0.0011
	(-0.82)	(1.52)	(-1.93)	(-0.87)	(1.36)	(2.10)	(0.21)	(0.50)
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
Industry×Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	15294	15294	15294	15294	9128	9128	9128	9128
Adj. R2	0.841	0.835	0.857	0.804	0.814	0.856	0.882	0.835

TABLE 4

Baseline Results: Product Market power vs. Labor Market power

This table presents regression results by disentangling the labor market power from the product market power. The product market peers are categorized based on 10-K Text-based Network Industry Classifications (TNIC) following Hoberg and Phillips (2010, 2015). LMP (EXCL. TNIC) is the weighted sum of a firm's labor market shares across all the firm's hiring labor markets, where labor market shares are constructed using the job posts of industry firms that compete in the local labor market but do not belong to the same group of produce market space. The data on 10-K TNIC is obtained from the Hoberg-Phillips Data. All variables are as defined in Table 1. All independent variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	BOOK	MKT	NET	NET	BOOK	MKT	NET	NET
Independent Variables	1	2	3	4	5	6	7	8
LMP (EXCL. TNIC)	0.0754**	0.0410**	0.0830**	0.0614***				
	(2.41)	(2.47)	(2.43)	(3.02)				
LMP					0.0627***	0.0698***	0.0805***	0.0945***
					(2.78)	(3.63)	(2.93)	(3.83)
SIZE	0.0218**	0.0466***	0.0633***	0.0369***	0.0369***	0.0476***	0.0852***	0.0448***
	(2.07)	(8.35)	(4.39)	(3.46)	(4.59)	(6.68)	(7.44)	(3.72)
M/B	-0.0123***	-0.0047***	-0.0151***	-0.0012	-0.0043**	-0.0080***	-0.0075***	0.0003
	(-3.40)	(-3.99)	(-3.82)	(-0.79)	(-2.27)	(-4.23)	(-3.68)	(0.15)
ROA	-0.1618	-0.0239**	-0.1791	-0.0176	-0.0243	-0.0282	-0.0548	0.0254
	(-0.94)	(-2.13)	(-1.05)	(-0.79)	(-0.64)	(-1.17)	(-1.26)	(0.82)
TANGIBILITY	0.1974***	0.0925***	0.2469***	0.1191***	0.0968***	0.0956***	0.1464***	0.0964***
	(2.84)	(6.25)	(3.70)	(6.43)	(4.77)	(7.83)	(6.33)	(5.29)
DIVIDEND	0.0097	-0.0088	0.0185	0.0047	0.0098	0.0035	0.0186	0.0169
	(0.94)	(-1.64)	(1.44)	(0.46)	(0.84)	(0.49)	(1.25)	(1.36)
AZ	0.0011	-0.0005	0.0006	-0.0000	-0.0007	-0.0015	-0.0016	-0.0044***
	(0.30)	(-1.43)	(0.18)	(-0.01)	(-0.45)	(-1.16)	(-0.90)	(-3.61)
ELS	-0.0015	0.0012	-0.0040*	-0.0009	-0.0013	0.0002	-0.0036*	-0.0017
	(-0.85)	(1.47)	(-1.96)	(-0.92)	(-0.70)	(0.21)	(-1.70)	(-1.29)
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
Industry×Year FE	Y	Y	Y	Y				
TNIC ×Year FE					Y	Y	Y	Y
N	15294	15294	15294	15294	13957	13957	13957	13957
Adj. R2	0.842	0.835	0.857	0.804	0.801	0.865	0.870	0.838

TABLE 5

Baseline Results: Control for Local Economic and Labor Market Conditions

This table presents regression results of the relation between a firm's labor market power and financial leverage by controlling for the local economic conditions and labor market shocks. % CHANGE IN LMS is calculated as the yearly percentage changes in the local labor force in a county. UNEMPLOYMENT is the percentage of unemployed relative to the local labor force in a given year. % EDU is the fraction of a county's population that has a bachelor's degree or higher in a given year. INCOME is the median household income in a county each year. The labor force and unemployment rate at the county-level are obtained from Local Area Unemployment Statistics of BLS. The percentage of educated population and household income are obtained from the Current Population Survey (CPS) from the U.S. Census Bureau. All other variables are as defined in Table 1. All independent variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A. Controlling local labor market characteristics

	BOOK	MKT	NET BOOK	NET MKT
Independent Variables	1	2	3	4
LMP	0.0461**	0.0465***	0.0611**	0.0652***
	(2.39)	(2.69)	(2.43)	(3.03)
SIZE	0.0212**	0.0470***	0.0626***	0.0365***
	(1.99)	(8.72)	(4.29)	(3.41)
M/B	-0.0123***	-0.0047***	-0.0152***	-0.0012
	(-3.41)	(-4.00)	(-3.83)	(-0.80)
ROA	-0.1622	-0.0235**	-0.1797	-0.0179
	(-0.94)	(-2.06)	(-1.05)	(-0.81)
TANGIBILITY	0.1964***	0.0920***	0.2456***	0.1179***
	(2.82)	(6.21)	(3.67)	(6.45)
DIVIDEND	0.0095	-0.0089*	0.0184	0.0047
	(0.94)	(-1.68)	(1.44)	(0.46)
AZ	0.0011	-0.0005	0.0007	-0.0000
	(0.30)	(-1.45)	(0.19)	(-0.00)
ELS	-0.0016	0.0012	-0.0041**	-0.0009
	(-0.87)	(1.48)	(-2.00)	(-1.00)
% CHANGE IN LMS	0.0021	-0.0113	0.0051	-0.0126
	(0.16)	(-1.15)	(0.42)	(-1.17)
UNEMPLOYMENT	-0.0928	-0.0024	0.0974	0.1744
	(-0.26)	(-0.01)	(0.23)	(0.63)
% EDU	-0.0016**	-0.0005	-0.0022**	-0.0017**
	(-2.08)	(-0.75)	(-2.43)	(-2.31)
INCOME	-0.0613	-0.1602***	-0.0322	-0.0385
	(-1.03)	(-2.97)	(-0.44)	(-0.76)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
Industry ×Year FE	Y	Y	Y	Y
N	15294	15294	15294	15294
Adj. R2	0.842	0.836	0.857	0.805

Panel B. Controlling local market shocks

Independent Variables	BOOK 1	MKT 2	NET BOOK 3	NET MKT 4
LMP	0.0698***	0.0615***	0.0987***	0.0891***
	(3.05)	(3.39)	(3.87)	(3.47)
SIZE	0.0318***	0.0457***	0.0799***	0.0457***
	(3.77)	(6.84)	(6.40)	(3.72)
M/B	-0.0044**	-0.0072***	-0.0075***	0.0016
	(-2.15)	(-3.97)	(-3.48)	(0.93)
ROA	-0.0202	-0.0196	-0.0508	0.0369
	(-0.52)	(-0.83)	(-1.15)	(1.23)
TANGIBILITY	0.1185***	0.0954***	0.1714***	0.1044***
	(6.05)	(7.54)	(7.96)	(5.47)
DIVIDEND	0.0042	0.0010	0.0138	0.0130
	(0.39)	(0.15)	(0.93)	(1.00)
AZ	0.0001	-0.0013	-0.0006	-0.0041***
	(0.05)	(-1.04)	(-0.35)	(-3.22)
ELS	-0.0018	0.0001	-0.0041*	-0.0017
	(-0.90)	(0.14)	(-1.91)	(-1.22)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
TNIC ×Year FE	Y	Y	Y	Y
N	13957	13957	13957	13957
Adj. R2	0.824	0.890	0.885	0.860

TABLE 6

Cross-sectional Analysis: Types of Talents

This table evaluates how the relationship between financial leverage and a firm's labor market power varies by the type of talent that firms hire. The first measure is the percentage of job posts targeting high-mobility occupations by a given firm. Occupational mobility is computed as the fraction of currently employed individuals in a given occupation who report a current occupation different from their last year's reported occupation, as per Kambourov and Manovskii (2008, 2009). The high mobility occupations are defined as those occupations above the median value of the occupation mobility each year. The annual individual occupation status data is from the Survey of Income and Program Participation (SIPP). The second measure is the skill similarity between the skills required by a firm's job posts and those required by the rest of the firms' job posts in the same geographical location. For each firm in a location, we compute the number of skills required by the firm within each skill cluster and the number of skills required by the rest of the firms in the same commuting zone within each skill cluster. Skill similarity is computed using the cosine similarity between the number of skills required by a given firm and the number of skills required by the rest of the firms in the same location across all the skill clusters. The data on skill requirement is obtained from Lightcast. HIGH LABOR MOBILITY (HIGH SKILL SIMILARITY) is a dummy taking a value of 1 for firms with the percentage of job posts targeting high mobility occupation (high skill similarity) above the location median and zero otherwise. The specification follows Table 2, column 5. All other variables are as defined in Table 1. All independent variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Independent Variables	BOOK 1	MKT 2	NET BOOK 3	NET MKT 4	BOOK 5	MKT 6	NET BOOK 7	NET MKT 8
LMP × HIGH LABOR MOBILITY	-0.0436**	-0.0549***	-0.0515**	-0.0463**				
	(-2.02)	(-2.98)	(-2.03)	(-2.08)				
LABOR MOBILITY	0.0075*	0.0050**	0.0091*	0.0044				
	(1.91)	(2.32)	(1.68)	(1.09)				
LMP × HIGH SKILL SIMILARITY					-0.0811***	-0.0688***	-0.0831**	-0.0570*
					(-2.88)	(-2.86)	(-2.09)	(-1.81)
SKILL SIMILARITY					-0.0024	-0.0099***	0.0006	-0.0173***
					(-0.33)	(-2.74)	(0.06)	(-2.62)
LMP	0.0671***	0.0710***	0.0879***	0.0872***	0.0709***	0.0627***	0.0836***	0.0666***
	(2.77)	(3.23)	(2.93)	(3.12)	(3.25)	(3.23)	(2.82)	(3.04)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
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
Industry×Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	14556	14556	14556	14556	13316	13316	13316	13316
Adj. R2	0.837	0.839	0.861	0.816	0.817	0.845	0.855	0.823

TABLE 7

Tax Shield vs. Labor Rigidity Reduction

This table evaluates whether firms with high labor market power increase financial leverage through higher debt capacity via tax shield or via labor rigidity reduction. Panel A presents the regression results of firms' ROA on firms' labor market power and other controls. The return on assets (ROA) is computed as the ratio of EBIT over total assets. Panel B presents the regression results of firms' earning volatility on firms' labor market power and other controls. Earnings volatility is computed as the standard deviation of income before extraordinary items plus depreciation and amortization to book assets over the past five years. Panel C presents the regression results of firms' changes in employment in response to the decline in profits conditional on a firm's labor market power. % EMP CHANGE is computed as the one-year percentage change in a firm's number of employees with positive percentage changes set to zero, following Serfling (2016). PROFIT DECLINE is a dummy variable that equals one if profitability is negative in a given year and zero otherwise. Profitability is measured as income before extraordinary items plus depreciation and amortization divided by the book value of assets. All other variables are as defined in Table 2. All independent variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A. Profitability

	Dependent Variable = ROA		
Independent Variables	1	2	3
LMP	0.0171	0.0163	0.0122
	(1.08)	(1.00)	(0.66)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
CZ FE	Y	Y	Y
Industry×Year FE	N	Y	Y
CZ ×Year FE	N	N	Y
Observations	15294	15294	15294
R^2	0.722	0.730	0.749

Panel B. Earnings volatility

	Dependent Variable = EARNINGS VOLATILITY		
Independent Variables	1	2	3
LMP	-0.0075**	-0.0059*	-0.0089***
	(-2.46)	(-1.82)	(-2.78)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
CZ FE	Y	Y	Y
Industry×Year FE	N	Y	Y
CZ ×Year FE	N	N	Y
Observations	15212	15212	15212
R^2	0.834	0.837	0.850

Panel c. Sensitivity of employment changes to profit declines

	Dependent Variable = %EMP CHANGE		
Independent Variables	1	2	3
LMP × PROFIT DECLINE	-0.1134**	-0.0946**	-0.1109*
	(-2.45)	(-2.01)	(-1.95)
PROFIT DECLINE	-0.0403***	-0.0293***	-0.0240**
	(-3.88)	(-2.83)	(-2.17)
LMP	0.0648**	0.0476	0.0561
	(2.26)	(1.49)	(1.45)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
CZ FE	Y	Y	Y
Industry×Year FE	N	Y	Y
CZ ×Year FE	N	N	Y
Observations	15225	15225	15225
R^2	0.353	0.384	0.441

TABLE 8

Amazon's HQ2 Difference-in-Difference Analysis

This table reports the regression results of the difference-in-difference analysis based on the announcement of Amazon's second headquarter (HQ2) in Crystal City, Arlington, Virginia. Panel B reports the estimates of the difference-in-difference analysis based on the treated and control firms that overlapped with the top five SOCs of Amazon's hiring before the entry of Amazon to Crystal City. Panel C reports the estimates of the granular difference-in-difference analysis. TREAT is an indicator variable that is set equal to one for treated firms located in CZ74 and its adjacent commuting zones and zero for the control firms locating in New York City. POST is an indicator variable that is set equal to one for the post-event period from 2019 to 2021 and zero for the pre-event period from 2014 to 2017. The event year 2018 is excluded from the analysis to avoid any confounding effect during the event year. The specification includes control variables, firm, year, local market, and industry × year fixed effects. All control variables are as defined in Table 1. All control variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A. Skill categories of Amazon's HQ hiring during 2014 – 2017

SOC	Description	Percentage
15-1132	Software Developers, Applications	0.227
11-2021	Marketing Managers	0.090
11-9199	Managers, All Other	0.084
15-1199	Computer Occupations, All Other	0.076
11-1021	General and Operations Managers	0.035

Panel B. Difference-in-difference analysis – Main specifications

	BOOK	MKT	NET BOOK	NET MKT
Independent Variables	1	2	3	4
TREAT × POST	-0.0634**	-0.0909***	-0.0829**	-0.1182***
	(-2.94)	(-9.04)	(-2.70)	(-3.81)
SIZE	0.0925**	0.0791***	0.1754***	0.0787
	(2.57)	(5.79)	(3.58)	(1.78)
M/B	-0.0101	0.0003	-0.0088	0.0353***
	(-0.58)	(0.03)	(-0.44)	(9.55)
ROA	-0.4675	-0.1723	-0.4765	-0.0529
	(-1.67)	(-0.82)	(-1.34)	(-0.13)
TANGIBILITY	0.4010***	0.2652**	0.5481***	0.4032**
	(3.99)	(3.46)	(5.32)	(3.04)
DIVIDEND	-0.0242	-0.0160	-0.0298	-0.0569
	(-0.43)	(-0.33)	(-0.45)	(-1.05)
AZ	0.0036	-0.0068	0.0010	-0.0119
	(0.60)	(-0.72)	(0.11)	(-1.08)
ELS	0.0204	0.0055	0.0057	0.0108
	(1.72)	(0.94)	(0.44)	(1.66)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

CZ FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
N	454	454	454	454
Adj. R2	0.867	0.882	0.912	0.868

Panel C. Difference-in-difference analysis – Granular specifications

Independent Variables	BOOK 1	MKT 2	NET BOOK 3	NET MKT 4
TREAT × AMAZON_HQ2_YR (-3)	0.0145	-0.0133	-0.0084	-0.0425
	(0.97)	(-1.48)	(-0.24)	(-1.81)
TREAT × AMAZON_HQ2_YR (-2)	0.0374	0.0081	0.0015	-0.0301
	(1.33)	(0.45)	(0.03)	(-1.32)
TREAT × AMAZON_HQ2_YR (-1)	0.0150	-0.0129	-0.0285	0.0207
	(0.74)	(-1.36)	(-0.76)	(0.38)
TREAT × AMAZON_HQ2_YR (+1)	0.0113	-0.0434***	-0.0350	-0.0904***
	(0.42)	(-3.62)	(-1.26)	(-3.89)
TREAT × AMAZON_HQ2_YR (+2)	-0.0415***	-0.0679***	-0.0664***	-0.0787***
	(-11.59)	(-7.01)	(-9.25)	(-4.72)
TREAT × AMAZON_HQ2_YR (+3)	-0.0270***	-0.0414***	-0.0434***	-0.0513***
	(-4.58)	(-7.36)	(-15.08)	(-5.32)
SIZE	0.0889**	0.0775***	0.1749**	0.0776
	(2.49)	(5.12)	(3.45)	(1.72)
M/B	-0.0111	-0.0004	-0.0091	0.0353***
	(-0.62)	(-0.04)	(-0.44)	(11.50)
ROA	-0.4715	-0.1774	-0.4786	-0.0674
	(-1.69)	(-0.85)	(-1.33)	(-0.16)
TANGIBILITY	0.3919***	0.2600**	0.5454***	0.3965**
	(3.95)	(3.47)	(5.37)	(2.91)
DIVIDEND	-0.0220	-0.0157	-0.0286	-0.0647
	(-0.38)	(-0.32)	(-0.41)	(-1.20)
AZ	0.0039	-0.0070	0.0004	-0.0108
	(0.65)	(-0.73)	(0.05)	(-0.92)
ELS	0.0197	0.0052	0.0054	0.0107
	(1.58)	(0.84)	(0.40)	(1.77)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
N	454	454	454	454
Adj. R2	0.869	0.885	0.913	0.870

Internet Appendix for

"LABOR MARKET POWER AND FINANCIAL LEVERAGE: EVIDENCE FROM ONLINE JOB POSTINGS"

This internet appendix presents additional results to complement those presented in the main body.

Section I presents additional tests to complement the panel regression analysis of leverage ratios on a firm's labor market power.

- Figure IA.1 presents the univariate tests on the relation between financial leverage and a firm's labor market power.
- Figure IA.2 presents the number of job posts by Amazon in commuting zone 74 and its adjacent commuting zone in Amazon's top five hiring occupations.
- Table IA.1 presents the robustness tests on the relation between financial leverage and a firm's labor market power using a measure constructed at the commuting zone level.
- Table IA.2 presents robustness tests on the relation between financial leverage and a firm's labor market power after excluding the year 2007.

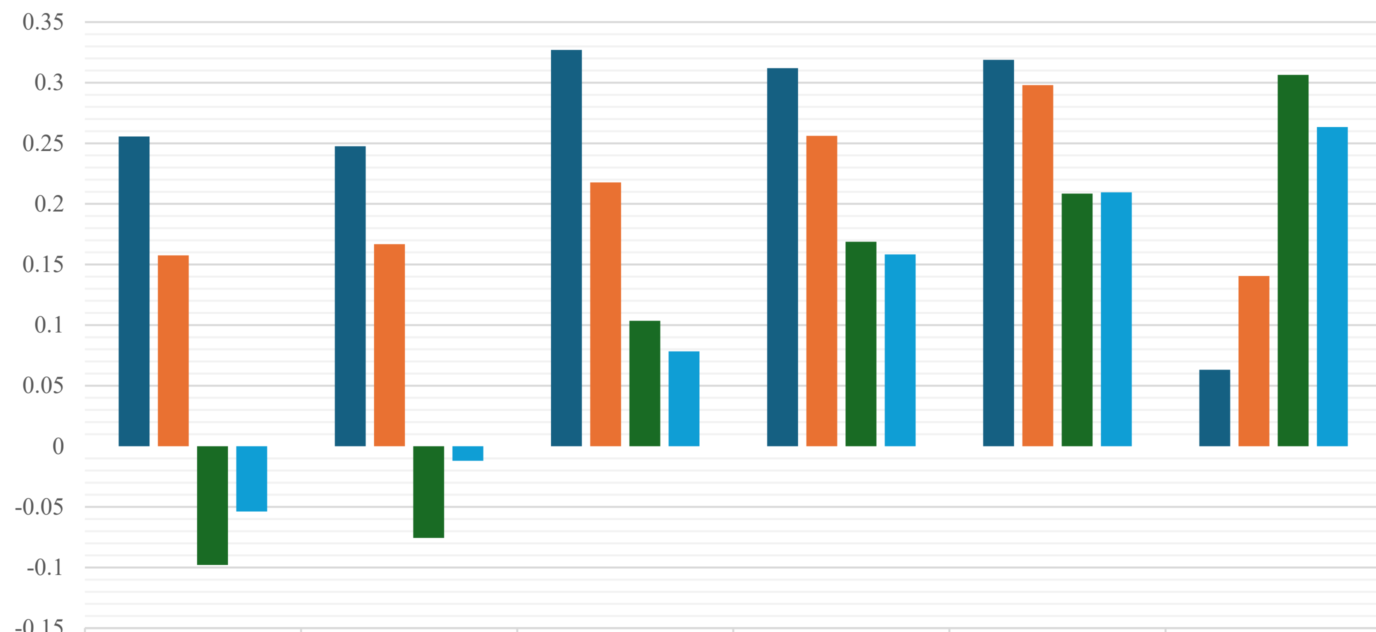
Section II discusses further analysis regarding our difference-in-difference regressions using the entry of Amazon as a quasi-natural experiment and then presents additional empirical evidence.

- Table IA.3 presents the difference-in-difference analysis of Amazon's HQ2 establishment using a sample of firms that compete with Amazon in the labor market but do not compete with Amazon in the product market.
- Table IA.4 presents the difference-in-difference analysis of Amazon's HQ2 establishment using firms located in 18 shortlisted U.S. cities as control firms.
- Table IA.5 reports the difference-in-difference analysis of Amazon's HQ2 establishment after controlling changes in the local labor market demand, supply, worker composition, and economic dynamics.
- Table IA.6 presents a validation test of the changes in labor market power of treated firms in the Crystal City area relative to control firms in NYC after the announcement of Amazon's HQ2 establishment.

Section I: Additional Analysis

Figure IA.1. Univariate Analysis

This figure presents univariate findings of the relation between leverage ratios and a firm's labor market power. The sample firms are sorted into five quintiles each year based on the firm's labor market power, as defined in Section 2.2. LMP is the weighted sum of the labor market shares across all the firm's hiring markets where local labor markets are defined at the U.S. commuting zone (CZ) × occupation (6-digit SOC) level. The bottom of the figure reports 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 labor market power. *** indicates the significance level at 1%.



	LMP (Q1 - Bottom)	LMP (Q2)	LMP (Q3)	LMP (Q4)	LMP (Q5 - Top)	Top – Bottom
Book	0.2557	0.2476	0.327	0.312	0.3189	0.0632 ***
Mkt	0.1575	0.1668	0.2178	0.2562	0.298	0.1405 ***
Net Book	-0.0979	-0.0756	0.1036	0.1688	0.2085	0.3064 ***
Net Mkt	-0.0538	-0.0119	0.0784	0.1584	0.2096	0.2634 ***

Book Mkt Net Book Net Mkt

Figure IA.2. Amazon's Job Posts Around the Announcement of HQ2 Establishment

This figure presents the number of job posts by Amazon in the commuting zone 74 and its adjacent commuting zone in Amazon's top five hiring occupations, including SOC 15-1132, 11-2021, 11-9199, 15-1199, 11-1021 during the period from 2014 to 2021.

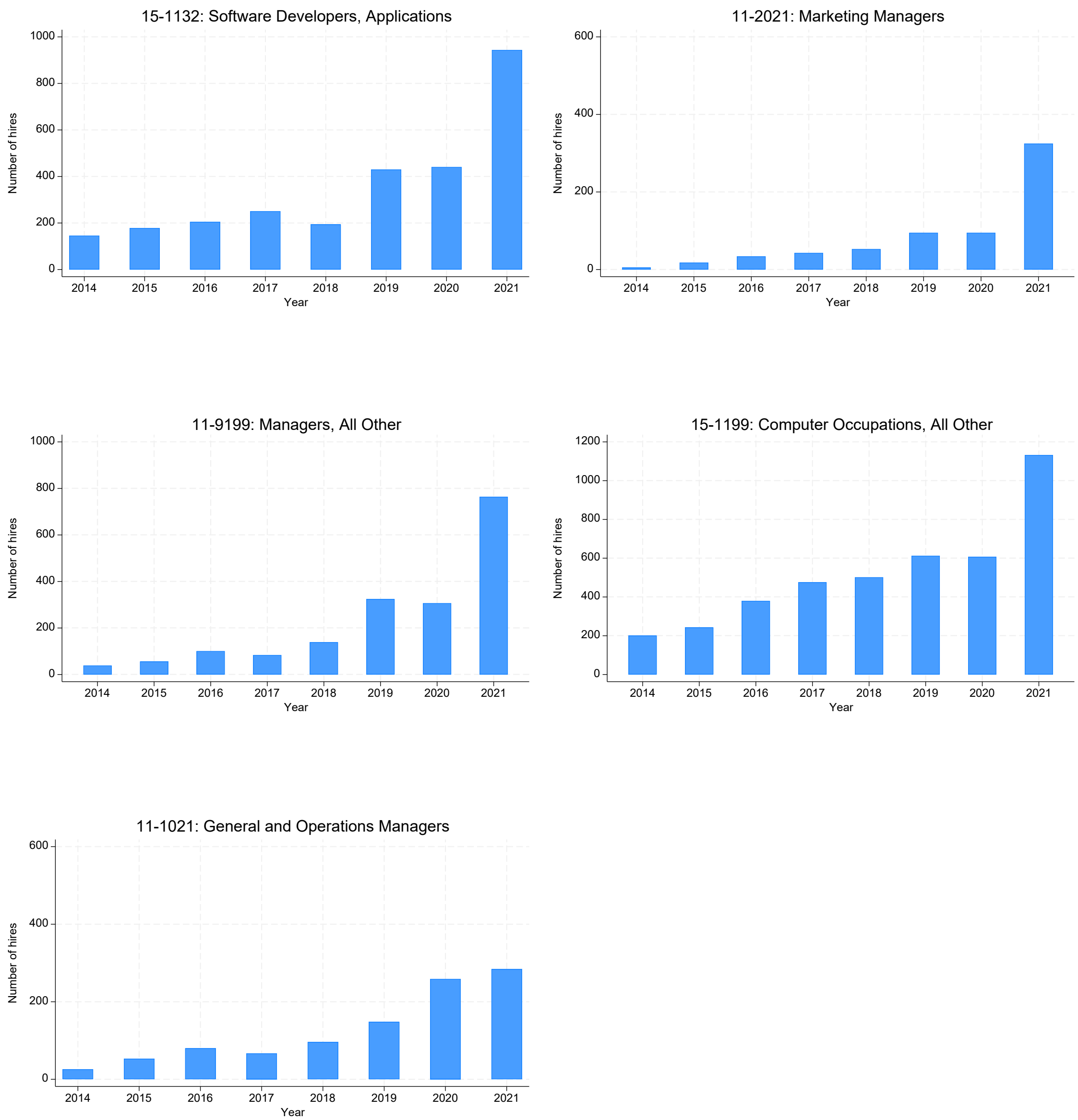


Table IA.1 Robustness: Alternative Measure

This table presents a robustness test on the relationship between a firm's labor market power and financial leverage using an alternative measure of employer power. $LMP\ (CZ)$ is the weighted sum of the labor market shares across all the firm's hiring markets where local labor markets are defined at the U.S. commuting zone (CZ) level. All control variables are as defined in Table 1. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt	(5) Book	(6) Mkt	(7) Net Book	(8) Net Mkt
LMP (CZ)	0.4333***	0.4100**	0.6639***	0.6815***	0.2403**	0.4437*	0.4512***	0.6726***
	(3.72)	(2.34)	(4.72)	(3.42)	(1.98)	(1.88)	(3.23)	(3.20)
SIZE	0.0291***	0.0466***	0.0714***	0.0396***	0.0365***	0.0471***	0.0847***	0.0441***
	(2.98)	(7.49)	(5.52)	(3.78)	(4.59)	(6.74)	(7.44)	(3.71)
M/B	-0.0111***	-0.0046***	-0.0136***	-0.0012	-0.0043**	-0.0080***	-0.0076***	0.0002
	(-3.86)	(-3.20)	(-4.34)	(-0.96)	(-2.29)	(-4.25)	(-3.71)	(0.14)
ROA	-0.1589	-0.0291**	-0.1724	-0.0146	-0.0246	-0.0287	-0.0553	0.0247
	(-0.95)	(-2.23)	(-1.03)	(-0.68)	(-0.66)	(-1.20)	(-1.28)	(0.80)
TANGIBILITY	0.1786***	0.1050***	0.2232***	0.1150***	0.0981***	0.0975***	0.1483***	0.0990***
	(2.83)	(7.48)	(3.62)	(6.13)	(4.81)	(7.90)	(6.39)	(5.42)
DIVIDEND	0.0197*	-0.0034	0.0277**	0.0113	0.0101	0.0039	0.0191	0.0174
	(1.80)	(-0.56)	(2.16)	(1.06)	(0.87)	(0.55)	(1.28)	(1.42)
AZ	0.0011	-0.0004	0.0006	-0.0001	-0.0006	-0.0014	-0.0016	-0.0044***
	(0.29)	(-0.96)	(0.15)	(-0.20)	(-0.43)	(-1.14)	(-0.88)	(-3.56)
ELS	-0.0014	0.0013	-0.0040*	-0.0006	-0.0013	0.0002	-0.0036*	-0.0017
	(-0.79)	(1.44)	(-1.97)	(-0.53)	(-0.68)	(0.26)	(-1.68)	(-1.26)
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
TNIC x Year FE					Y	Y	Y	Y
N	15294	15294	15294	15294	13957	13957	13957	13957
Adj. R2	0.835	0.809	0.851	0.788	0.801	0.865	0.870	0.838

Table IA.2 Robustness: Excluding Year 2007

This table presents regression results of leverage ratios on a firm's labor market power and relevant control variables by excluding the year of 2007. All variables are as defined in Table 1. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt
LMP	0.0456**	0.0462**	0.0586**	0.0653***
	(2.18)	(2.53)	(2.14)	(2.78)
SIZE	0.0273***	0.0422***	0.0667***	0.0351***
	(2.64)	(7.49)	(4.63)	(3.58)
M/B	-0.0119***	-0.0042***	-0.0145***	-0.0009
	(-3.34)	(-3.95)	(-3.70)	(-0.63)
ROA	-0.1886	-0.0227**	-0.2059	-0.0198
	(-1.08)	(-2.02)	(-1.20)	(-0.90)
TANGIBILITY	0.2343***	0.0921***	0.2801***	0.1133***
	(3.47)	(6.19)	(4.22)	(5.66)
DIVIDEND	0.0094	-0.0113**	0.0166	-0.0009
	(0.87)	(-2.02)	(1.31)	(-0.09)
AZ	0.0021	-0.0004	0.0017	0.0002
	(0.58)	(-1.12)	(0.50)	(0.21)
ELS	-0.0011	0.0013	-0.0036	-0.0008
	(-0.55)	(1.53)	(-1.60)	(-0.89)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
N	14571	14571	14571	14571
Adj. R2	0.846	0.840	0.861	0.807

Section II: Further Analysis of Amazon HQ2 Experiment

Local spillover effects?

Amazon received significant subsidies and incentives to establish its second headquarters, HQ2, in Crystal City, Arlington, Virginia. These include a direct cash grant of $23 million from Arlington County over 15 years, based on the growth of local transient occupancy taxes. Additionally, Virginia offered $195 million for transportation projects to improve mobility in Northern Virginia, including enhancements to Metro stations at Crystal City and Potomac Yard. Further, local investments include over $570 million from Arlington and Alexandria for additional transportation infrastructure, such as rail connections and transit facilities. [37] These incentives are contingent on Amazon meeting specific targets, such as creating 25,000 jobs with an average wage of over $150,000 per year and occupying a specific amount of office space.

A potential concern about our findings may be that these government subsidies and incentives have a spillover effect on local firms, subsequently affecting their financial policy. Amazon's presence may create new jobs, attract a diverse pool of skilled professionals nationwide, raise wages for local employees, change the composition of employment, and eventually spur economic and business growth.

To address this issue, our tests now directly control such spillover effects. First, we control the changes in labor demand due to Amazon's HQ2 establishment – i.e., Amazon's entry may lead to the creation of new jobs in the Crystal City area, particularly in occupations of high demand by Amazon, such as Software Developers, Marketing Managers, General Managers, Computer Occupations, and Operational Managers. We measure the changes in labor demand using the job

[37] See https://www.virginiabusiness.com/article/northern-virginia-lands-a-big-chunk-of-amazons-second-corporate-headquarter/.

post data from Lightcast and labor force data from Local Area Unemployment Statistics of BLS.[38] Specifically, we compute the job vacancy rate ($Job\ vacany\ rate$) as our first measure of labor demand, which is defined as the number of job posts divided by the sum of the total number of job posts and labor force in a given commuting zone. This measure captures the changes in overall labor demand around the event of Amazon's entry into the Crystal City area. Then we compute the logarithm of the total number of job posts in the top five hiring occupations of Amazon in a commuting zone each year ($Job\ post\ overlapped$),[39] which capture the changes in labor demand for occupations intensively hired by Amazon. The results for book (market) leverage are shown in columns (1) – (2), Panel A (Panel B) of Table IA.5. As we can see, the coefficient for $Job\ vacany\ rate$ is negative and significant and coefficient for $Job\ post\ overlapped$ is mostly insignificant. After a set of controls for labor demand, our results for $Treated_i \times Post_t$ remain intact.

Second, we control the changes in labor supply due to Amazon's HQ2 establishment. For example, due to high-paying job opportunities, skilled professionals may reallocate to the Crystal City area after Amazon's HQ2 announcement. The presence of Amazon HQ2 enhances the overall appeal of Crystal City as a burgeoning tech and business hub, further motivating professionals seeking career advancement and dynamic work environments to consider relocation. To capture the effect of Amazon's entry on labor supply, we measure the changes in local labor supply using the labor force participation rate in a given commuting zone ($Labor\ force\ participation\ rate$). Then, we repeat our difference-in-difference analysis by including the changes in labor supply in the regression. The result on book leverage (market leverage) is presented in column (3), Panel A

[38] The labor force data are obtained from Local Area Unemployment Statistics of BLS: https://www.bls.gov/lau/tables.htm.

[39] The top five hiring occupations of Amazon include the following occupations codes: "11-1021", "11-2021", "11-9199", "15-1132", and "15-1199".

(Panel B) of Table IA.5. The coefficients for $Labor\ force\ participation\ rate$ are insignificant and the coefficients for $Treated_i \times Post_t$ remain negative and highly statistically significant, irrespective of book or market leverage considered. These findings suggest that our results remain robust after controlling for the changes in labor demand and supply.

Third, we control changes in labor market dynamics due to Amazon's HQ2 establishment, such as changes in employment, wages, and composition of the workforce. For example, Amazon's entry is expected to lead to an increase in employment and wages, particularly in Amazon's top hiring occupations. To capture such an effect, we measure the growth rate in total employment ($Employment\ growth$) and growth rate in average wages ($Wage\ growth$) in a given commuting zone each year using occupational employment and wage data from Occupational Employment and Wage Statistics (OEWS).[40] Furthermore, we control the composition of the workforce as Amazon's entry also affects its composition – i.e., local workers with compatible skills may move to occupations that are in high demand following Amazon's entry. To measure the changes of labor composition, we compute the growth rate in the total employment ($Empl\ growth\ overlapped$), growth rate in average wages ($Wage\ growth\ overlapped$), the percentage of employment in the top five hiring skill categories of Amazon ($\%\ Empl\ overlapped$). We further construct the percentage of employment in the top hiring occupation families of Amazon in a given commuting zone each year ($\%\ Empl\ SOC2$).[41] Then, we repeat our difference-in-difference analysis by including the changes in employment, wages, and workforce composition in the regression. Columns (4) – (8) of Table IA.5 show that coefficients for $Treated_i \times Post_t$ remain negative and highly significant, suggesting that changes

[40] See https://www.bls.gov/oes/.

[41] The top hiring occupation families of Amazon are as follows: 11-Management, 13- Business and Financial Operations, 15- Computer and Mathematical, 41-Sales and Related.

in labor market power capture a dimension different from other labor market dynamics and have a significant impact on the firms' financial policy.

Lastly, Amazon's HQ2 establishment may attract new firms into the local market, such as startups that are Amazon's potential funding or acquisition targets (Jin, 2019).[42] Therefore, we include the business startups' growth and innovation activities as controls in our difference-in-difference analysis. $Business\ startup\ growth$ is the annual growth rate of the number of business establishments in a given commuting zone from County Business Patterns (CBP) datasets of Census Bureau.[43] Growth in innovation activities ($Innovation\ Growth$) is measured using the annual growth rate in the number of patents applied for by all firms in a given commuting zone.[44] The results are presented in column (9) of Table IA.5. Again, the coefficients for $Treated_i \times Post_t$ are still negative and highly significant after controlling for overall business growth and firm innovation activities. Taken together, these results suggest that our findings are robust to the control for the local labor market dynamics and economic perspectives brought by Amazon's entry.

A collateral channel? The effect on real estate investment and prices

Another concern of our findings is that Amazon's entry into Crystal City leads to an appreciation of local residential and commercial real estate values and consequently affects firm's use of debts. An influx of high-paying tech jobs in the Crystal City region attracted a diverse pool of skilled professionals from across the country, leading to an increase in the local population and a rise in the demand for housing and services.[45] To the extent that firms usually use real estate as collateral

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[42] Xue (2022) finds that the entry of top innovative firms positively impacts the innovation activities of incumbent firms through the knowledge spillover effects.
[43] https://www.census.gov/data/datasets/2021/econ/cbp/2021-cbp.html.
[44] The patent data is obtained from KPSS patent dataset: https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
[45] Indeed, Qian and Tan (2021) document the welfare consequence of high-skilled firm entry on incumbent residents. They estimate the effect of the firm entry on incumbent residents' consumption, finances, and mobility using 391

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). In other words, 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.

Has the labor market power of incumbent firms changed? Validation tests

We assume that Amazon's entry into the Crystal City area reduced the labor market power of incumbent firms. We now perform two validation tests to assess the quality of this assumption. We analyze (i) changes in labor market power of treated firms relative to the control firms at the commuting zone level after Amazon's entry and (ii) changes in labor market power at the commuting zone × SOC level between treated and control firms after Amazon's entry. We restrict the construction of labor market power measures for treated firms within the treated area (i.e., CZ 74 and adjacent area) as Amazon's entry only impacts the labor market power of incumbent firms in the affected region.

We start by analyzing the changes in the labor market power of treated firms in the Crystal City area relative to control firms of NYC after Amazon's entry. Specifically, we reconstruct the labor market power of treated firms (control firms) as the weighted sum of market shares of treated firms in CZ 74 and adjacent areas (control firms in NYC), where market shares are defined at the commuting zone level:

$$LMP(CZ)_{i,t}^{Treat} = \sum_{CZ \in Crystal\ City} \frac{V_{i,CZ,t}}{V_{i,t}} \times S_{i,CZ,t}. \qquad \text{(IA.1a)}$$

$$LMP(CZ)_{i,t}^{Control} = \sum_{CZ \in NYC} \frac{V_{i,CZ,t}}{V_{i,t}} \times S_{i,CZ,t} \qquad \text{(IA.1b)}$$

high-skilled firm entries in the U.S. from 1990-2010. They find that high-incumbents, especially homeowners benefits and low-skilled incumbents on average benefit less.

where $S_{i,CZ,t} = V_{i,CZ,t}/V_{CZ,t}$ measures firm i's power (or market share) in the commuting zone (CZ), $\frac{V_{i,CZ,t}}{V_{i,t}}$ is the share of firm i's hiring in a given commuting zone CZ.

Following the equation (2). Then we run the following regression:

$$LMP(CZ)_{i,t} = \delta Treated_i \times Post_t + \gamma' Z_{i,t-1} + \rho' W_{c,t} + \alpha_i + \tau_t + \varphi_{cz} + \theta_{jt} + \varepsilon_{i,t} \tag{IA.2}$$

where $LMP(CZ)_{i,t}$ is the labor market power of treated or control firms, $Treated_i$ equals 1 for the firms located in the Crystal City area and 0 for those located NYC. $Post_t$ equals 1 for period from 2019-2021 and 0 for period from 2014-2017. $W_{c,t}$ is a vector of labor market and economic characteristics, including measures of labor demand, labor supply, employment, wages, employment composition, business establishment startups, and innovation activities. θ_{jt} is the industry-times-time fixed effect, which captures the time-varying industry shocks.

The results are reported in Panel A of Table IA.6. They document that, after controlling for all the correlated changes brought about by Amazon's entry, the coefficients for $Treated_i \times POST_t$ remain highly negative and significant, irrespective of the different controls included. This implies that Amazon's entry into the Crystal City area has significantly reduced the local labor market power of incumbent firms, as expected.

Next, we perform our second validation test using the labor market power of treated firms (control firms) defined at the commuting zone × SOC level. Specifically, we construct the labor market power of incumbent firms as follows:

$$LMP_{i,t}^{Treat} = \sum_{m \in Crystal\ City} \frac{V_{i,m,t}}{V_{i,t}} \times S_{i,m,t}. \tag{IA.3a}$$

$$LMP_{i,t}^{Control} = \sum_{m \in NYC} \frac{V_{i,m,t}}{V_{i,t}} \times S_{i,m,t}. \tag{IA.3b}$$

Where $S_{i,m,t} = V_{i,m,t}/V_{m,t}$ measures firm i's power (or market share) in the local labor market (m), $\frac{V_{i,m,t}}{V_{i,t}}$ is the share of firm i's hiring in a given local labor market.

We follow the same specification as in equation (10) but use the second measure of labor market power as our dependent variable. The results are reported in Panel B of Table IA.6. As expected, after a set of controls for the correlated changes brough about by Amazon's entry, the coefficients for $Treated_i \times POST_t$ are also negative and highly significant as the first validation test. This suggests that the entry of Amazon significantly lowers the labor market power of incumbent firms in Crystal City area relative to the control firms in NYC. These tests further confirm the validity of our premise and support Amazon's announcement of HQ2 establishment as a quasi-natural experiments for labor market power.

Table IA.3 Amazon's HQ2: Excluding product market peers

This table reports the regression results of the difference-in-difference analysis based on the announcement of Amazon's second headquarter (HQ2) in Crystal City, Arlington, Virginia using a sample of firms that do not compete with Amazon in the product market. The firms that belong to the same product market peers based on TNIC are excluded from the sample. All control variables are as defined in Table 1. All control variables are lagged for one period. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Difference-in-difference analysis – Main specifications

	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)
Treated × Post	-0.0615***	-0.1203***	-0.1056***	-0.1321**
	(-3.80)	(-5.15)	(-3.69)	(-2.96)
SIZE	0.0832**	0.0787***	0.1738**	0.0409
	(2.40)	(5.96)	(3.36)	(0.75)
M/B	-0.0128	-0.0017	-0.0115	0.0213***
	(-0.53)	(-0.20)	(-0.42)	(4.77)
ROA	-0.6211	-0.2310	-0.5996	0.0439
	(-1.48)	(-0.77)	(-1.47)	(0.11)
TANGIBILITY	0.5773**	0.4113**	0.6631**	0.2143
	(3.13)	(3.01)	(3.48)	(1.00)
DIVIDEND	-0.0430	-0.0314	-0.0486	-0.0317
	(-0.69)	(-0.56)	(-0.70)	(-0.58)
AZ	0.0078	-0.0139	0.0093	-0.0097
	(0.73)	(-1.21)	(0.75)	(-0.98)
ELS	0.0262*	0.0064	0.0101	-0.0051
	(2.09)	(0.77)	(0.81)	(-0.80)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
N	377	377	377	377
Adj. R2	0.854	0.881	0.913	0.893

Panel B: Difference-in-difference analysis – Granular specifications

	Book	Mkt	Net Book	Net Mkt
	(1)	(2)	(3)	(4)
Treated × AmazonHQ2 (-3)	0.0086	0.0054	-0.0303	-0.0377
	(0.38)	(0.25)	(-0.61)	(-1.45)
Treated × AmazonHQ2 (-2)	0.0343	0.0165	-0.0015	-0.0298
	(1.37)	(0.56)	(-0.03)	(-0.92)
Treated × AmazonHQ2 (-1)	0.0232	0.0084	-0.0040	0.0636
	(0.49)	(0.33)	(-0.07)	(0.70)
Treated × AmazonHQ2 (+1)	0.0113	-0.0621***	-0.0561	-0.0912***
	(0.38)	(-5.12)	(-1.72)	(-6.07)
Treated × AmazonHQ2 (+2)	-0.0412***	-0.0752***	-0.0773***	-0.0781***
	(-8.25)	(-6.05)	(-8.78)	(-5.33)
Treated × AmazonHQ2 (+3)	-0.0264***	-0.0465***	-0.0474***	-0.0509***
	(-11.33)	(-8.65)	(-25.03)	(-4.86)
SIZE	0.0793*	0.0760***	0.1700**	0.0394
	(2.24)	(5.57)	(3.12)	(0.74)
M/B	-0.0134	-0.0021	-0.0119	0.0219***
	(-0.55)	(-0.24)	(-0.42)	(5.39)
ROA	-0.6317	-0.2391	-0.6150	0.0162
	(-1.50)	(-0.79)	(-1.50)	(0.04)
TANGIBILITY	0.5644**	0.3997**	0.6476**	0.2068
	(2.96)	(2.86)	(3.28)	(0.97)
DIVIDEND	-0.0461	-0.0331	-0.0508	-0.0443
	(-0.75)	(-0.58)	(-0.74)	(-0.86)
AZ	0.0089	-0.0132	0.0105	-0.0073
	(0.87)	(-1.13)	(0.83)	(-0.67)
ELS	0.0256*	0.0059	0.0098	-0.0049
	(1.97)	(0.68)	(0.77)	(-0.76)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y
N	377	377	377	377
Adj. R2	0.856	0.884	0.914	0.896

Table IA.4 Difference-in-difference analysis: 18 shortlisted cities

This table reports the estimates of the difference-in-difference analysis where control firms located in the 18 shortlisted U.S. cities with hiring overlapped with the top five skill categories hired by Amazon before the entry of Amazon to Crystal City. All variables are as defined in Table 1. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

	(1) Book	(2) Mkt	(3) Net Book	(4) Net Mkt	(5) Book	(6) Mkt	(7) Net Book	(8) Net Mkt
Treated × AmazonHQ2 (-3)	0.0183	0.0041	-0.0081	-0.0023	-0.0145	-0.0298	-0.0807	-0.0880**
	(1.26)	(0.35)	(-0.26)	(-0.12)	(-0.58)	(-1.48)	(-1.20)	(-2.60)
Treated × AmazonHQ2 (-2)	0.0314	0.0203	-0.0203	0.0055	-0.0086	-0.0179	-0.0876	-0.0538
	(1.30)	(1.13)	(-0.50)	(0.33)	(-0.25)	(-0.57)	(-1.26)	(-1.19)
Treated × AmazonHQ2 (-1)	0.0358	0.0133	-0.0115	0.0383	0.0144	-0.0196	-0.0570	0.0279
	(1.17)	(0.64)	(-0.25)	(0.93)	(0.34)	(-0.61)	(-0.80)	(0.41)
Treated × AmazonHQ2 (+1)	0.0345	-0.0430**	0.0011	-0.0515**	0.0752	-0.0521	0.0440	-0.1054*
	(1.25)	(-2.22)	(0.03)	(-2.20)	(1.62)	(-1.07)	(0.66)	(-1.87)
Treated × AmazonHQ2 (+2)	-0.0057	-0.0404***	-0.0261	-0.0379**	-0.0276	-0.0694***	-0.0694*	-0.0842***
	(-0.31)	(-3.27)	(-1.24)	(-2.80)	(-0.97)	(-3.52)	(-2.05)	(-3.57)
Treated × AmazonHQ2 (+3)	-0.0181	-0.0297***	-0.0395**	-0.0379***	-0.0384*	-0.0475***	-0.0686**	-0.0682***
	(-1.29)	(-2.99)	(-2.42)	(-3.71)	(-1.80)	(-3.19)	(-2.44)	(-3.52)
SIZE	0.0939***	0.0492**	0.1537***	0.0544*	0.1559***	0.1059***	0.2192***	0.0804**
	(3.41)	(2.23)	(3.09)	(1.97)	(3.77)	(4.69)	(3.38)	(2.16)
M/B	-0.0032	-0.0057	0.0006	0.0123*	0.0000	-0.0006	0.0013	0.0122**
	(-0.23)	(-1.07)	(0.03)	(2.05)	(0.00)	(-0.12)	(0.07)	(2.56)
ROA	-0.0380	-0.0504	-0.0702	0.0067	0.0915	0.0214	0.0399	0.1470
	(-0.16)	(-0.43)	(-0.25)	(0.03)	(0.34)	(0.18)	(0.12)	(0.56)
TANGIBILITY	0.3640***	0.1093	0.4401***	0.2335**	0.4185***	0.1514	0.5147***	0.2463
	(3.43)	(1.31)	(3.34)	(2.33)	(3.24)	(1.61)	(3.29)	(1.59)
DIVIDEND	-0.0066	-0.0023	0.0011	-0.0179	-0.0187	-0.0023	0.0163	-0.0125
	(-0.19)	(-0.09)	(0.02)	(-0.54)	(-0.57)	(-0.08)	(0.27)	(-0.60)
AZ	-0.0138	-0.0117	-0.0147	-0.0136	-0.0269*	-0.0233***	-0.0268	-0.0246**
	(-0.84)	(-1.28)	(-0.65)	(-1.10)	(-1.86)	(-3.03)	(-1.30)	(-2.81)
ELS	-0.0037	-0.0023	-0.0099	0.0059	-0.0041	-0.0017	-0.0110	0.0032
	(-0.27)	(-0.42)	(-0.87)	(1.01)	(-0.28)	(-0.34)	(-0.84)	(0.54)
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
Industry×Year FE	Y	Y	Y	Y				
TNIC ×Year FE					Y	Y	Y	Y
Observations	814	814	814	814	618	618	618	618
R^2	0.819	0.865	0.868	0.788	0.795	0.880	0.871	0.805

Table IA.5 Amazon's HQ2 Difference-in-Difference Analysis: Alternative channels

This table reports the estimates of the difference-in-difference analysis after controlling changes in the local labor market demand, supply, worker composition, and economic dynamics.

To control changes in labor demand and supply, we construct the following measures: *Job vacancy rate* is computed as the number of job posts divided by the sum of the total number of job posts and labor force in a given commuting zone. *Job posts overlapped* is the logarithm of the total number of job posts posted by all firms in a given commuting zone in the top five hiring occupations of Amazon (occupation codes: "11-1021", "11-2021", "11-9199", "15-1132", and "15-1199") . *Labor force participation rate* is calculated as the labor force divided by the working-age population in a given commuting zone. The labor force data are obtained from Local Area Unemployment Statistics of BLS (https://www.bls.gov/lau/tables.htm).

To control changes in employment, wages, and workforce composition, we use the following measures: *Employment growth* is the annual growth rate of total employment in a given commuting zone. *Wage growth* is the average annual growth rate of wages across all occupations hired in a given commuting zone. *Empl growth overlapped* (*Wage growth overlapped*) are the total employment growth rate (average wage growth rate) in top five hiring occupations of Amazon. *% Empl Overlapped* is the percentage of employment in top five hiring occupations of Amazon. *% Empl (SOC2 = 11)* is the percentage of employment in the two-digit SOC family "11" in a given commuting zone. *% Empl (SOC2 = 13)*, *% Empl (SOC2 = 15)*, and *% Empl (SOC2 = 41)* are defined analogously. The occupational employment and wage data is obtained from Occupational Employment and Wage Statistics (OEWS) (https://www.bls.gov/oes/).

To control the growth in business start-ups and innovation activities, we construct the following measures: *Business start-up growth* is the annual growth rate in the number of business establishments in a year in a given commuting zone from County Business Patterns (CBP) datasets of the Census Bureau (https://www.census.gov/data/datasets/2021/econ/cbp/2021-cbp.html). Growth in innovation activities are measured using the annual growth rate in the number of patents applied for by all firms in a given commuting zone. The patent data is obtained from KPSS patent dataset (https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data).

All specifications include the control variables, firm, year, local market, and industry × year fixed effects. All other control variables are as defined in Table 1. Standard errors are clustered at the commuting zone level. ***, **, * indicate the significance level at 1%, 5% and 10% respectively.

Panel A: Book Leverage

	(1) Book	(2) Book	(3) Book	(4) Book	(5) Book	(6) Book	(7) Book	(8) Book	(9) Book
Treated × Post	-0.0634**	-0.0420**	-0.0662**	-0.0484**	-0.0715**	-0.0705***	-0.0242*	-0.0436***	-0.0588**
	(-2.94)	(-2.83)	(-2.55)	(-3.00)	(-3.05)	(-3.66)	(-2.05)	(-4.02)	(-2.96)
Job vacancy rate		-0.0373**		-0.0358**					
		(-3.23)		(-2.67)					
Job posts overlapped			-0.0106						
			(-0.61)						
Labor force participation				-1.2489					
				(-1.18)					
Employment growth					0.1255**				
					(3.49)				
Wage growth					-1.8997*				
					(-2.31)				
Empl growth overlapped						0.0685**			
						(2.73)			
Wage growth overlapped						-0.5512**			
						(-3.18)			
% Empl Overalpped							20.1304**		
							(2.62)		
% Empl (SOC2 = 11)								0.5518	
								(1.51)	
% Empl (SOC2 = 13)								-0.2909	
								(-0.62)	
% Empl (SOC2 = 15)								0.1861	
								(0.42)	
% Empl (SOC2 = 41)								0.6362	
								(0.60)	
Business startups growth									0.0127
									(0.96)
Innovation growth									0.0097
									(1.47)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm + Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	454	454	454	454	454	454	454	454	454
R^2	0.867	0.871	0.867	0.871	0.867	0.867	0.868	0.868	0.867

Panel B: Market leverage

	(1) Mkt	(2) Mkt	(3) Mkt	(4) Mkt	(5) Mkt	(6) Mkt	(7) Mkt	(8) Mkt	(9) Mkt
Treated × Post	-0.0909***	-0.0734***	-0.0859***	-0.0767***	-0.0939***	-0.0858***	-0.0602***	-0.0661**	-0.0901***
	(-9.04)	(-8.83)	(-8.58)	(-5.27)	(-10.71)	(-6.67)	(-4.50)	(-3.26)	(-10.12)
Job vacancy rate		-0.0305***		-0.0297***					
		(-5.75)		(-4.29)					
Job posts overlapped			0.0187						
			(0.61)						
Labor force participation				-0.6550					
				(-0.56)					
Employment growth					-0.0355				
					(-1.03)				
Wage growth					-1.2955				
					(-1.79)				
Empl growth overlapped						-0.0770*			
						(-2.01)			
Wage growth overlapped						0.1516			
						(0.35)			
% Empl Overalpped							15.7531**		
							(2.57)		
% Empl (SOC2 = 11)								0.1899	
								(0.70)	
% Empl (SOC2 = 13)								0.2217	
								(0.32)	
% Empl (SOC2 = 15)								-0.3151	
								(-0.63)	
% Empl (SOC2 = 41)								1.0838	
								(0.94)	
Business startups growth									0.0036
									(0.50)
Innovation growth									0.0088*
									(2.25)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm + Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	454	454	454	454	454	454	454	454	454
R^2	0.882	0.886	0.882	0.886	0.882	0.882	0.883	0.883	0.882

Table IA.6 Amazon's HQ2 Difference-in-Difference Analysis: Validation Test
This table reports the estimates of the validation test on the changes in employer power. All measures are as defined in Table 1 and Table IA.6.

Panel A: Employer power measured at CZ level

	(1) LMP(CZ)	(2) LMP(CZ)	(3) LMP(CZ)	(4) LMP(CZ)	(5) LMP(CZ)	(6) LMP(CZ)	(7) LMP(CZ)	(8) LMP(CZ)	(9) LMP(CZ)
Treated × Post	-0.0035***	-0.0034***	-0.0044***	-0.0036**	-0.0035***	-0.0035***	-0.0037***	-0.0022**	-0.0043***
	(-3.66)	(-4.14)	(-3.87)	(-3.49)	(-3.68)	(-3.86)	(-3.51)	(-2.53)	(-3.83)
Job vacancy rate		-0.0003		-0.0002					
		(-0.75)		(-0.61)					
Job posts overlapped			-0.0031**						
			(-3.39)						
Labor force participation				-0.0502					
				(-1.15)					
Employment growth					-0.0003				
					(-0.22)				
Wage growth					-0.0005				
					(-0.01)				
Empl growth overlapped						0.0013			
						(0.68)			
Wage growth overlapped						0.0091			
						(1.18)			
% Empl Overalpped SOCs							-0.0992		
							(-0.98)		
% Empl (SOC2 = 11)								0.0259*	
								(2.23)	
% Empl (SOC2 = 13)								-0.0075	
								(-0.32)	
% Empl (SOC2 = 15)								0.0051	
								(0.40)	
% Empl (SOC2 = 41)								0.0530	
								(1.61)	
Business startups growth									-0.0017**
									(-2.71)
Innovation growth									0.0005
									(1.47)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm + Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	454	454	454	454	454	454	454	454	454
R^2	0.507	0.508	0.508	0.508	0.507	0.508	0.507	0.512	0.511

Panel B: Employer power measured at SOC level

	(1) LMP	(2) LMP	(3) LMP	(4) LMP	(5) LMP	(6) LMP	(7) LMP	(8) LMP	(9) LMP
Treated × Post	-0.0057**	-0.0054***	-0.0065***	-0.0058**	-0.0057***	-0.0057***	-0.0062**	-0.0038**	-0.0070***
	(-3.43)	(-3.86)	(-3.52)	(-3.34)	(-3.53)	(-3.63)	(-3.32)	(-2.50)	(-3.65)
Job vacancy rate		-0.0005		-0.0004					
		(-0.80)		(-0.68)					
Job posts overlapped			-0.0031**						
			(-2.43)						
Labor force participation				-0.0763					
				(-1.13)					
Employment growth					0.0002				
					(0.09)				
Wage growth					-0.0158				
					(-0.33)				
Empl growth overlapped						0.0024			
						(0.75)			
Wage growth overlapped						0.0177			
						(1.32)			
% Empl Overalpped SOCs							-0.2590		
							(-1.38)		
% Empl (SOC2 = 11)								0.0403*	
								(1.98)	
% Empl (SOC2 = 13)								-0.0155	
								(-0.39)	
% Empl (SOC2 = 15)								0.0109	
								(0.53)	
% Empl (SOC2 = 41)								0.0740	
								(1.29)	
Business startups growth									-0.0028**
									(-2.67)
Innovation growth									0.0008
									(1.42)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm + Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	454	454	454	454	454	454	454	454	454
R^2	0.548	0.548	0.548	0.548	0.548	0.548	0.548	0.551	0.551