Labor Market Power and Firm Financial Flexibility*

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Abstract

Using a novel database representing the near-universe of US online job postings, we examine the role of firms' labor market power on financial flexibility and corporate policy. Validating our measure, within a county-occupation, high labor market power is associated with lower posted wages. The measure is associated with lower cash holdings and market beta, and higher Tobin's Q and profitability. The relation is stronger in industries that are labor intensive, which have high worker mobility, and low rates of unionization and attributable to market-share over high skill jobs. High labor market power firms react less to passages of enforcement of non-compete laws, which we use as a difference-in-differences strategy. The result is consistent with the idea that high labor market power firms are less exposed to shocks in the labor market.

KEY WORDS: Labor Market Power, Firm Financial Flexibility and Corporate Policy, Vacancy Postings

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1 Introduction

Firms compete with each other not only in the product market, but also the labor market. Each firm differs in their relative share of the labor market and in the competitiveness of the labor market they face. In other words, firms differ in their monopoly power in the labor market. When a firm's labor market power is high, the firm is in a superior bargaining position to the employee and vice versa. In this paper, we introduce a novel dataset representing the near universe of online job postings in the US. Using this dataset, we attempt to quantify firms' relative labor market power, and study the interaction between labor market power and firms' financial flexibility and corporate policy.

Market power of firms has attracted much attention among academics, practitioners and policy makers. Industrial organization as a field focuses on studying the interaction between product market power and firm outcomes. Policy makers have expressed concerns about industry monopolies and their negative effect on consumer welfare. Moreover, there is growing concerns about the increasing mark-up and product market power of large firms (De Loecker and Eeckhout, 2017). However, relatively little attention has been put on firms' labor market power. In fact, to our best knowledge, although there are the beginnings of studies which speak to concentration in the labor market, there has not been any research that documents a firm's labor market power, and specifically the extent to which the labor market power affects corporate policy.

We lever a unique dataset that covers the near-universe of online job postings in the U.S. in 2007 and 2010-2016. We hand-match the dataset to Compustat. We construct each publicly listed firm's labor market power as its relative-to-rival market share of job postings. Intuitively, our measure captures a firm's local labor market share compared to the competitiveness of the local labor market. We find that there is a large cross-sectional dispersion in firms' labor market power. Moreover, the labor market power is highly persistent. Splitting our sample into two periods, the rank correlation across the two periods is 65%.

We conjecture that firms with high labor market power are less exposed to labor market shocks, because these firms have more bargaining power and thus can easily adapt. This results in the firms behaving as if they are less risky. Consistent with our hypothesis, firms with high labor market power hold less cash, have lower market beta, and have higher leverage. The economic magnitude on cash is that a standardized deviation movement in our preferred specification is 5% of a standard deviation movement in cash. Moreover, we find that these firms have higher Tobin's Q and have higher profitability, suggesting that investors understand that the firms with high labor market power are safer and that this market power is a positive firm fundamental.

Furthermore, our finding shows that high labor market power firms pay lower wages on average. This analysis serves two purposes for our paper. First, it is a validation of our measure: we expect that posted wages are negatively related to firms' labor market power. Second, the finding differentiates our measure from a demand-based explanation. In the presence of a demand shock, a firm would rejoin an increase to its opportunity set by hiring more workers. Our measure of market power is increasing in the number of postings a firm has. Moreover, such a demand shock may also explain a firm's financial outcomes, such as its Tobin's Q. Further, in the presence of a demand shock, we would expect the effect on wages to be positive.

However, instead of a positive relation, we find a negative relation between labor market power and posted wages. We make this inference at the level of a specific vacancy, controlling for SOC6(job)-quarter, industry-quarter fixed effects and job characteristics primarily based on several measures of the number of demanded skills. Further, our main effect is highly robust controlling for a variety of other measures at the firm-level that could be correlated to size or opportunities: a firm-fixed effect, Tobin's Q, and many polynomial order terms of job postings and log-assets. The negative relation to wages suggests that our main results are not driven by a demand shock, and are likely capturing a firm's market power in the labor market.

We conduct a series of cross-sectional tests in order to verify our mechanism. We expect that the effect of labor market power is more pronounced amongst labor intensive industries and industries where firms bargaining power is low. We perform cross-sectional analysis using three variables previously documented in the labor and finance literature. These are the capital-to-labor ratio, unionization rate, and labor mobility, all measured at the industry-year level. We find that the effect of labor market power (1) is less relevant among high capital-to-labor ratio industries, (2) is weaker in high unionization rate industries, and (3) is stronger among high labor mobility industries. This is after controlling for industry-by-year fixed effects, suggesting no other industry-level variation drives our results.

Then, we directly test the idea that firms with high labor market power are less exposed to labor market shocks. We consider a specific type of labor market shocks: a shock to mobility. Specifically, we exploit the passage of court cases which strengthened the enforcement of pre-existing non-compete laws. These court cases were originally documented in Jeffers (2017). In her study, strengthened non-compete enforcement impacts worker mobility and startup creation. We examine the interaction between labor market power and the passage of non-compete laws, and hypothesize that the firms with high labor market power are less sensitive to the passage of non-competes. We define exposure to the non-compete laws as the fractional share of one's postings in a treated state, where treatment is defined as a state-year after a court case which strengthens non-compete enforcement. Overall, we find evidence in support of our hypothesis. Unconditionally, the passage of an increase in the enforceability of noncompete laws leads to a decrease in firms' cash-holding and vice versa. For firms in the highest quintile of labor market power, there is no effect. For firms in the lowest quintile, their cash holdings are lower.

This paper contributes to the literature at the intersection of labor economics and finance. In this paper, we try to provide a firm-level labor market power measure by calculating each firm's relative-to-rival share of job postings. Although research on firms' labor market power is scarce, there is a large literature on product market concentration. The canonical measure of concentration is to calculate the Herfindahl-Hirschman Index (HHI) and the n-firm concentration ratios, referring to the fraction of a market held by the largest n players.

Applying the intuition of product market competition to the labor market, some recent papers (Azar, Marinescu, and Steinbaum, 2017; Benmelech, Bergman, and Kim, 2018; Azar, Marinescu, Steinbaum, and Taska, 2018) try to carry this idea to the labor market by calculating the HHI index of the labor market within geography and occupation.[1] The general findings in these papers are that labor market concentration tends to be high and that local wages are depressed in high labor market concentration regions. We differ from this literature by providing a firm-level measure of labor market power. Our measure derives from labor market concentration, but examines a firm's relative position. The relative position confers the firm labor market power, which has consequences for financial flexibility and corporate policies.

The labor economics literature approaches the issue of labor market power in the lens of minimum wage, unionization, and labor mobility. The literature focuses on issues that are specific to each individual firms instead of the labor market structure that are common to all firms. Chen, Kacperczyk, and Ortiz-Molina (2011) find that firms in high unionization rate industries have higher cost of equity. Donangelo (2014) shows that firms in high labor mobility industries are riskier. We view our paper as complement to this literature by providing a measure that embeds the labor market power of the firm relative to the competitiveness of the overall local labor market.

Our research also contributes to the growing literature that exploits vacancy posting data. Most of the studies in this literature have used aggregate vacancy data from the Bureau of Labor Statistics' Job Openings and Labor Market Turnover (JOLTS) survey. Davis, Faberman, and Haltiwanger (2013) use plant-level data from the JOLTS survey to study vacancy-filling rate. The JOLTS data lacks information on the characteristics of a given vacancy or the firm that is posting it. Some studies (e.g. Shen and Kuhn, 2013; Marinescu, 2017; Rothwell, 2014) have used small subsamples of vacancy posting level data. Recently,

[1]Earlier works that focus on particular industries include Staiger, Spetz, and Phibbs (2010), Falch (2010), Ransom and Sims (2010), Matsudaira (2014).

Hershbein and Kahn (2018) and Ballance, Modestino, and Shoag (2016) used detailed job posting data to study the "upskilling" phenomenon since the Great Recession.

In the finance literature, Liu (2017) utilizes detailed vacancy posting data and finds that firms' vacancy posting rate contains information about risk premia in the cross-section. Our paper constructs a new firm-level measure of labor market power using detailed vacancy posting data, based on the intuition that a firm's position relative to its rivals confers it an advantage in a market.

The rest of the paper is structured as following. Section 2 introduces our data. Section 3 presents our main results. and Section 4 concludes.

2 Data

2.1 Burning Glass Technologies Data

The principal data for this study is furnished by Burning Glass Technologies (BGT). BGT collates data from company websites and job boards. BGT provides job postings for the years 2007 and 2010-2016. Each posting provides the name of employer, job title, location of the intended job, and job requirements – skills, certifications, educational requirements – as inferred through natural language processing software, wages if available, and location. BGT spends considerable effort normalizing the data, de-duplicating postings across job boards.

In addition to the posting itself, BGT is unique in providing skills required by postings. Capitalizing on this advantage, Hershbein and Kahn (2018) and Ballance, Modestino, and Shoag (2016) use BGT data to study why firms appear to be "upskilling", increasing the number of skills demanded in job postings. We exploit this feature in a few of our analyses.

Prior papers using this data have suggested it is the near universe of online job postings, and representative of US industries as a whole. Because sample representativeness may affect inferences from the BGT data, Hershbein and Kahn (2018) compare industry level data from the BGT to statistics from the Bureau of Labor Statistics' Occupational Employment Statistics series. Through a number of key statistics, Hershbein and Kahn (2018) conclude favorably that the BGT data is broadly representative of the broader US population at the industry level. Because the job-postings are online, however, there is overrepresentation of occupations involving computer and math skills, and occupations involving management, healthcare, business and financial operations, and under-representation at the low-skill occupations and in general any occupation for which online job search is still not the modus operandi of the industry. Therefore, in some of our sub-sample analyses, our analysis will be "within-occupation".

However, despite the broad industry representation, it is worth noting two key coverage issues. First, approximately 1/3rd of posts omit the employer. This is likely because many job-postings are pulled from job boards, where either employers can choose to or are not allowed to disclose themselves. We throw these out because our analysis is relative to the top employers in a given locale. Also, many postings omit salaries, either because salaries are negotiable or firms prefer to redact for competitive reasons. Our salary-level analysis must be interpreted with caution. However, the goal of our salary analysis is to validate our forthcoming measure of market power – which should correlate to lower posted wages – and to distinguish against a possible counter-explanation for our main finding.

2.2 Sample construction and summary statistics

Our focus will be on publicly listed firms. BGT spends considerable effort normalizing the names in job-postings so that employers can be tracked. To construct our sample of publicly listed firms, we hand-matched the 25,000 most common employer names and then supplemented by exact-name matching to a database of names using point-in-time Compustat identifiers. The bulk of our sample comes from hand-matching.

[Table 1 about here]

Table 1 describes our yield from this exercise and plots the count of firms (publicly linked and otherwise), the number of job postings, the percentage of firms listing a wage, and wage information. We match around 4000 Compustat firms per year. Each year there are approximately 20 million job postings in our sample that pass basic sample filters, and applying those same filters about 5 million belong to publicly listed firms. The wages for these listed jobs are roughly the same, but publicly listed firms only list wages 5% of the time whereas the unconditional reporting rate is around 15%.

[Table 2 about here]

Turning to Table 2, we now analyze the characteristics of these firms. One key issue is sampling bias. Table 2 suggests that the key moments of our variables are roughly similar between sample firms (Panel A) and the overall Compustat North-America universe (Sample B). Generalizations which emerge are that firms well-covered by BGT appear to be lager, hold slightly less cash, and are somewhat older than the Compustat universe firm. This difference is sensible if firms which post on job-boards are generally more mature. However, on the basis of sample medians or sample means, the firms do not look dramatically different.

2.3 Measure of Labor Market Power

We example our calculation in Table 3 and report summary statistics thereof in Table 4. This section describes the construction of our measure of labor market power. We quantify a firm's labor market power as its relative-to-rival market share in the job posting market. Because labor market is relatively localized, we regard each metro area as a distinct labor market. The absolute labor market share ($s_{i,m}$) for firm i in county m is defined as firm i's number of postings over the total amount of postings in county m. We define the competitiveness (c_m) of county m as the concentration ratio or the top 4 companies' labor market share of county m. The labor market power for firm i in county m is calculated as the $s_{i,m}/c_m$. For firms operate in multiply counties, we calculate the weighted average labor market power as the firm-level labor market power, where the weight is the number of postings. Our measure captures the idea that a small share firm's labor market power is different in a competitive labor market compared to a concentrated labor market. Intuitively, for given labor market share, the labor market power of firm i is larger in a competitive labor market relative to a concentrated labor market.

Here, we give a simple example to illustrate the construction of our measure. Company A operates in two counties: County 1 and County 2. In total, there are 100 postings and 200 postings in County 1 and County 2, respectively. Company A posts 20 postings in County 1 and 50 postings in County 2. The top 4 companies post 60 postings in County 1 and 120 postings in County 2. Then, Company A's labor market power measure is $\frac{1}{3}$ for County 1 and $\frac{5}{12}$ for County 2. The overall labor market power of Company A is the weighted average of the two measures.

More formally, the baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t. Denote the $top4_{c,t}$ as the sum of all postings by the top 4 posters in a county. This is analogous to the numerator in the canonical four-firm concentration ratio. Then a firm's labor market share in a county is:

$$LMS_{i,c,t} = \frac{postings_{i,c,t}/postings_{c,t}}{top\ 4_{c,t}/postings_{c,t}} = \frac{postings_{i,c,t}}{top\ 4_{c,t}} \tag{1}$$

The firm-level measure is weighted by postings in the county. Therefore,

$$LMS_{i,t} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} \times LMS_{i,c,t} \tag{2}$$

We winsorize this measure to ensure that our results are not driven by outliers. We also run a $\log(1 + LMS_{i,c,t})$ as a specification check. In our analysis, these two measures are standardized to be of the unit norm for facilitating interpretation. In robustness checks, we re-define the geographic aggregation unit to be the metropolitan statistical area as measured by BGT. The results are quantitatively and qualitatively similar. We also for some analysis decompose the measure only using high-skill and low-skill postings, where following literature convention, high-skill postings are ones that either require 5 years of experience or a bachelor's degree.

[Table 3 about here]

Having exampled our calculation method, we now explore the summary statistics thereof for the whole sample. Table 3 presents our summary statistics. We present four versions of the main metric. Column (1) presents the county-level measure. The average posting-weighted market share is 1%, while the median is .4%. The 95th percentile share is 3.5%. This suggests that market power measures have fairly large right tails, suggesting that a log-specification may be useful for robustness. Column (2) represents a metro area result. Given the larger geographical expanse, it is not surprising that in levels, the market power measures are quantitatively lower. We then also decompose the measure into high-skill and low-skill labor. We define low-skill and high-skill labor based on having a masters degree or 5 years of experience, following prior literature. We then segment the job-posting universe into these two categories re-calculate our market power measures. We use this decomposition later to examine whether or not our effect is mainly driven by more-mobile high-skilled labor or low-skilled labor.

3 Main Results

This section presents our results. In Section 3.1, we first investigate the relation between our measure of market power and firm financial policy. In section 3.3, we then decompose the market power measure further in the cross-section. Throughout this section on Main Results, we present robustness checks to dispel alternative interpretations of our findings.

We run annual panel regressions of the following form:

$$Y_{i,t} = \alpha_{industry,t} + \beta_1 \times LMS_{i,t} + controls + \epsilon_{i,t} \tag{3}$$

Because we find that our labor market power measure is highly persistent and our panel is relatively short, we do not run within-firm analysis. The measure is highly persistent. For example, splitting the sample into the first four years and the second four years (2007, 2010-2013), the rank correlation at the employer level is 65%. This suggests that being a high market power firm in the first-half of the sample and second-half of the sample. Thus, most of our results are driven by across-firm analysis. When we do run within-firm analysis, our statistical reliability of our estimates is hindered but point in the same direction.

The controls we use are (unless used as an outcome variable), firm age, cash, profitability (NI/AT in Compustat), log sales growth, sales-to-assets, Tobin's Q and log assets. To account for the correlation between market power (a measure of relative to demand) and the firm's overall demand, we control for the log number of postings and the fraction the firm comprises of the overall national labor market. In some specifications we overload our analysis with 2nd and 3rd order polynomials of postings and log assets to account for these size effects. We explore several robustness checks for this last endogeneity concern throughout this section. In particular, in Section 3.2 we will explore the relation between our measure of market power and wages. To the extent a demand shock is endogenous to both the level of postings and the level of cash or our other financial policy variables, the prediction would be that such a demand shock has a negative correlation with wages. We present evidence of the opposite, suggesting our mechanism and not the presence of a demand shock. Then we present cross-sectional tests that support our preferred explanation that labor market power confers a firm an advantage particularly when labor has more bargaining power.

3.1 Corporate Policy

The first variable we investigate is the firm's cash-to-assets ratio. High cash holdings are broadly regarded as a measure of conservatism. We expect the relation between the measure of labor market power and cash holdings to be negative, because market power over the labor market allows firms to acquire workers when necessary, and/or, moreover, to pay those workers relatively less. Both of these channels would reduce their required financial flexibility.

[Table 4 about here]

Table 4 reports our results on cash. Our variable of interest are z-scored, that is to say it has unit standard deviation and zero mean. We present six columns, the evenly numbered columns specifying our measure of market power as log(1+x) and the other presenting the raw ratio. Both sets of results are quite similar. Columns 1 and 2 reveal that the relation between a standard deviation unit increase in market power and cash is 70 basis points. this corresponds to a reduction of 4% of the mean cash holdings.

Columns 3 and 4 repeat Columns 1, adding 2nd order polynominal terms to log-assets and log-postings as control variables and additionally a 3rd order polynomial. The rationale for doing this is that our measure of market power may be correlated with the firm's unconditional size – firms which are larger are relatively larger compared to workers where they operate. However, overloading the specification with higher order terms barely affects our estimates, dropping our main estimate by 10% when applying third order polynomials.

In Columns 5 and 6 of Table 5, we now subset firms removing utilities and financial firms per industry standard. These firms are treated specially by many corporate finance researchers because the meaning of cash could be different for a financial firm. Although our analysis is within industry-year, which accounts for mean-differences in the way cash is reported, there could be substantive differences in the relation between market power and cash. Thus, in Columns 5 and 6 we remove such firms, removing about 1/4th of the sample. If anything, our relation becomes larger in economic magnitudes. This suggests our results are invariant to the presence of financial and utility firms. For the remainder of the paper, we prefer the tabulation involving all firms to maximize cross-industry variation particularly for our cross-sectional tests. However, we have tabulated, finding quantitatively and qualitatively similar results that on balance strengthen our inferences in some of our additional tests as often as they weaken them.

We next perform analysis on market beta, debt/assets, Tobin's Q and profitability. For debt, we predict that firms which have more operating flexibility can take on more debt. We expect that firms that have more operating flexibility and lower operating leverage have lower market beta. For Tobin's Q, we expect that firms which have more market power over the labor market have higher firm valuations. We couch endogeneity concerns until later sections.

[Table 5 about here]

Table 5 reports the results. In this analysis we carried forward Column (1) of the prior analysis in Table 5. Columns (1) and (2) report our results on debt. The results are negative but insignificant. Leverage may be confounded by a number of other factors overwhelming the relation to market power. Column (3) explores the relation with market beta. Here, the reduction in market beta for a unit increase in market power is 3.1% of a standard deviation in market beta, and about 1% of the mean. This magnitude is similar to that for cash holdings. These results suggest that across a few different measures of corporate financial policy, firms which comprise a larger fraction of the local labor market behave in a way that they have more financial flexibility.

Columns (4) and (5) explore the relation between winsorized and logged Tobin's Q. We present two specifications to moderate the existence of outliers on Tobin's Q. A standard deviation increase of market power correlates with an increase in Tobin's Q of .035, which is 0.28 of a standard deviation. Column (6) adds net income-to-assets as an outcome variable. This economic magnitude is the largest of all outcome variables explored.

It suggests that firms which have higher market power are 10% more profitable. Interpreting our proxy of market power through our preferred lens, this suggests that firms which have more market power are also more profitable as consequence of their market power. This would be consistent with the idea that labor has a lower share of the firm's overall profits as a function of the firm's hiring market power.

3.2 Wages

We next explore the relation between wages in the job posting required by the firm and our proxy of market power. Crucially, this analysis serves two purposes for our paper. First, it provides validation of our measure. If it is indeed a proxy of market power, we expect a negative relation between the firm's market power and the posted wages.

Second, such an analysis differentiates our measure from a demand-based explanation. Thus far, we have shown a positive relation between our proxy of market power and Tobin's Q and profitability. One alternative explanation may be a positive shock to a firm fundamental causes the firm to demand more labor and also have high Tobin's Q and high profitability. For example, our result could be partly driven by a boom to sales prospects. This shock would generate higher postings, which generates a higher measure of market power because it has postings in the numerator. This would be particularly plausible if such a shock was contained in a particular geography. Even though we control for the number of postings, there may be specification error. However, we argue that such a shock to the firm's opportunities would be consistent with higher wages, not lower wages. Thus our wage analysis is crucial in validating our preferred interpretation of our results.

We perform two types of analysis. First, we perform firm-level analysis. Second, we perform posting-level analysis. The two analyses are parallel but implicitly weight firms on an equal and a value-weighted basis respectively.

There are two issues with performing analysis on wages. The first is that firms hire heterogenous types of workers. Thus, the characteristics of the job must be accounted for when doing analysis on wages. Luckily, we have a rich set of posting characteristics in our dataset.

The second key issue is that postings often omit salaries. It is unclear for what reasons the postings redact salaries. Thus, the quantitative magnitudes emerging from this forthcoming analysis must be interpreted with caution. In fact, as our summary statistics show, relative to the average firm, publicly listed firms are far more likely to redact a wage. However, our main goal of this analysis is to validate a directional prediction. To the extent the redaction of wages is not endogenous to geographic market power over the labor market, our analysis should be valid.

For analysis at the posting level, we examine the relation between two types of proxies for market power. We first look at the relation between county share of postings deflated by the posting counts of the top 4 employers (e.g. county-level market power) and aggregate national market power. Then we look at the national level measure. We expect the same prediction and simply show both for robustness. County-level market power may be more accurate in that it isolates the local labor market conditions. On the other hand, if the firm is capable of cross-subsidizing hiring needs in two different counties, it is possible that overall firm level market power is what matters. That is, being able to hire in one market may mean lower wages posted in another market.

We now report the results of Table 6, which is analysis at the posting level. We prefer this analysis because it allows us to control for specific job-level characteristics, which impact wages directly.

[Table 6 about here]

As for the specification, we control for firm characteristics, county-quarter fixed effects, job (Standard Occupation Code 6 digit)-quarter fixed effects, the number of postings the firm has in that quarter nationally, and the log number of skills in the job posting. We also include a firm fixed-effect in this analysis because now the firm is being observed at multiple geographies, allowing us variation to estimate more precisely and partial out any time-invariant firm-level determinants of wages.

Columns (1) and (2) perform the analysis in which the main variable of interest is the fraction of postings a firm has in a county relative to the top 4. Column (1) specifies the regression using county fixed effects and Column (2) reports firm fixed effects. Although the unit of analysis has changed, we keep firm-level clustering. County-level clustering actually improves our results dramatically, but we remain consistent across specifications. Thus, in columns (3-6), we stick with firm-level clustering.

Columns (3) - (6) report a moderately reliable relation between firm-level market power and reported log-wages, controlling for a battery of firm characteristics and posting characteristics. The magnitude of column (3) is -0.035, which is an economically small magnitude (less than 1% of salary) but reliably negative. Columns (5) and (6) add a firm fixed effect which chips away partly at the estimate in economic magnitude, but if anything increases reliability of the relation to market power. This suggests firm-specific noise is partly driving wage levels.

As a complementary robustness check, Table 7 Panel B reports our results at the firm-level. Note that the observation count drops because if a firm has no postings that year, we remove it the firm-year from our analysis. In columns (1) - (4) we examine raw wages without adjusting for posting characteristics. In columns (5) and (6), we average wages after filtering the job posting for job characteristics. To obtain this filtering, every month, we run sector and occupation code fixed effects and also various log-counts of skills (the count of skills, finance skills, computer skills, software skills and soft skills). This suggests the estimates are purged of sector and job-level variation, and skill requirements within the same sector or job.

The results of Appendix A1 are not extremely reliable, but provide suggestive evidence that the relation between our measure of market power and wages is negative. All estimates are negative. Columns (5) and (6) are marginally precise, with column (5) being estimated significantly at the 5% level and (6) right below that threshold.

Taken together, the posting-level and the firm-level results confirm our main hypothesis that the relation between our measure of market power and wages is negative. The analysis confirms our main intuition that a measure of market power should be reliably negatively related to wages. It also suggests that a demand-shock to firms is not driving the main finding.

3.3 Cross-Sectional Variation

In this section, we decompose our main finding in Section 3.1 above in the cross-section. The cross-sectional variation should be consistent with a greater significance of labor market power where firms are generally more labor-dependent (capital-labor ratio and among high-skill workers), for firms where labor is more mobile, and for firms which are more subject to unions.

First, we examine firms with high capital-to-labor ratio at the industry-year level based on 4-digit industries. The intuition is that firms in capital-intensive industries will be less reliant on labor, and as a result the observed relation should dissipate partially. Table 7 reports our results. The capital/labor ratio is standardized to the unit norm. Columns (1) and (2) indicate that firms with higher market power are hold more cash if they are in a labor intensive industry, suggesting a mitigated role for market power for less capital-intensive firms. The observed relation to Tobin's Q also appears to be lower for capital-intensive firms but the estimate is unreliable.

[Table 7 about here]

Next, we examine the role of labor unions. We obtain the industry-level unionization rate and interact this variable with cash holdings and Tobin's Q. Table 8 reports our results. The results suggest that the market power proxy bears a lower relation to financial policy in industries where there is a higher unionization rate. A standardized unit increase in the unionization rate reduces the relation to cash holdings and Tobin's Q by approximately 1/3rd. This diluted effect is consistent across all four of our specifications and statistically very reliable.

[Table 8 about here]

Next, we examine the role of labor mobility. We proxy for it two ways. We first use high-skill labor as a proxy. Second we obtain industry-level mobility measures from prior work. We assume that high-skill labor is more mobile than low-skill labor. We define high-skill labor based on having a master degree and 5 years of experience. We then re-calculate the labor market power measures segmenting the job universes into high-skilled and low-skilled, and then form our original metrics for each.

[Table 9 about here]

Table 9 reports our results based on high-skill and low-skill measure. Table 10 reports results using the worker mobility from Donangelo (2014). In Table 9, we essentially horse-race the high-skill and low-skill market power measures and measure them against our outcome variables. The basic idea is that the high-skill numbers appear to matter more in explaining firm outcomes. Column (1) and (2) suggest that market power in the high-skill market has a slightly larger economic magnitude in explaining cash holdings. Columns (3) and (4) show that high-skill labor market power is positively correlated to Tobin's Q, whereas low-skill labor market power is not and is if anything slightly negative. Finally, high-skill labor is related to firm's market beta and there is no reliable relation of low-skill labor. Table 10 explores the mobility measure at the industry level. The results suggest that market power matters more in high-mobility industries. Columns 1 and 2 suggest that mobility increases the effect of market power on cash holdings by 50%. Columns 3 and 4 suggest similar economic magnitudes for the relation between market power and Tobin's Q. This suggests that the relation of market power to firm outcomes is larger exactly in contexts where it may be expected.

[Table 10 about here]

3.4 Interaction with Non-Compete Laws

Our next analysis is to examine the interaction between postings and the passage of worker mobility restrictions due to the enforcement of non-compete laws. The increase in enforcement over our sample period originates from Jeffers (2017). Jeffers (2017) documents court cases in which enforcement of non-competes either increased in strength or decreased which had an evident impact worker mobility and startup creation. Specifically, firms appeared to invest more at the expense of worker mobility and startups. Because, presumably, the passage of court cases is immune from the economic environment that may drive politics and legislation, these events can be presumed to be valid natural experiments. The setting is particularly suitable to our study because there are instances for both increase and decrease of enforcement of non-competes in the sample. Therefore, we can study whether high labor market power firms are less sensitive to these shocks in the labor market. We refer readers to Jeffers (2017) for detail about the construction and timing of the changes in the corporate non-compete laws.

Premised on this identification strategy, we hypothesize that firms with low labor market power are more exposed to shocks of the labor market. Therefore, we expect the effect of passages of enforcement of non-compete laws to be more pronounced in low labor market power firms.

In this analysis, we interact our measure of market power with exposure to non-compete law passage. To determine exposure, we calculate the fraction of postings in exposed states in a given year. This exposure is an interaction variable which we expect will amplify the effect of market power.

[Table 11 about here]

Table 11 reports our results. For this analysis, to increase the power we have in using market power to explain cash holdings, we create indicator variables for low and high market power, which refer to being in the annual low or high market power bins. We report specifications emphasizing these indicator variables as well as our original variables which yield null results.

Turning to Columns (1) and (2), we find that the unconditional relation between non-competes and cash holdings is negative. If workers are less mobile, firms can operate more safely and have to hold less precautionary cash. Then, turning to the indicator variables for high market power and low market power, it suggests that relative to other firms, high market power firms hold less cash and low market power firms hold more cash.

Finally, we examine the cross-sectional relation between market power and cash is positive for high-market-power firms and negative for low-market-power firms. Column (1) suggests that the effect of CNC laws on high market power firms is zero. This is because these firms have a large fraction of the local labor market, and so the effect of increased restricted worker mobility is inconsequential. For firms with low market power, worker mobility restrictions decrease holdings.

Columns (3) and (4) suggest that the differential effect on low market power firms is strong enough to survive within-firm fixed effects. Columns (5) and (6) indicate that our original measures of market power are not reliably different from zero, although the direction is positive which is consistent with the idea that higher market power firms are differentially less affected by CNC enforcement.

The evidence here provides the suggestion that enforcement of non-competes, which restrict labor mobility, affects firms with low labor market power than high labor market power firms, consistent with our hypothesis that high market power firms are less exposed to shocks in the labor market. The findings are consistent with our hypothesis that high labor market power firms are less exposed or sensitive to shocks in the labor market. In other words, firms with high labor market power are safer.

3.5 Difference of Labor Market Power from Labor Market Concentration

One concern is that our results are not capturing something different from recent literature that has documented the labor market concentration drives wages. Our analysis on wages is within-county-quarter, suggesting that county-level labor market concentration is not driving our results. This is because the county-quarter fixed effects means that overall labor market concentration is partialed out, and the main effect comes from a firm's relative to rival positioning.

To extend and differentiate our analysis further, we tabulate results controlling for market concentration in the counties in which the firm operates. Analogously to before, for each county c we calculate the HHI of employer shares in that county, and then aggregate on a posting-weighted basis for a firm to the national level.

More formally, this is:

$$HHI_{i,c,t} = \sum_{i \in firms} \left(\frac{postings_{i,c,t}}{postings_{c,t}} \right)^2 \tag{4}$$

The firm-level measure is weighted by postings in the county. Therefore,

$$HHI_{i,t} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} \times HHI_{i,c,t} \tag{5}$$

We horse-race this measure and interact the measure. Appendix A.2 reports the results. Columns (1) and (2) present our baseline analysis which suggests that controlling for concentration in the markets in which the firm operates, our measure is still significant. The magnitude is reduced by 1/3rd.

Columns (3) and (4) interact the measures. The cross-term of the two suggests the interaction reverses the main effect of our market power proxy on cash. In economic terms, this suggests that market power matters less for cash particularly when the market is already concentrated. This echoes our analysis earlier with non-competes, suggesting that the strengthening of non-competes is less meaningful when the firm already has high share of the local labor market demand. Thus, to the extent that labor market concentration captures the overall exposure of the firm, our measure uniquely captures the firms' relative market power.

4 Conclusion

In this paper, we use the near universe of online job postings in the United States to study the extent of labor market power. Building off the intuition of the four-firm concentration ratio, our measure captures the fraction of job postings by the top 4 employers. Our measure appears to explain lower wages, within county-quarter and within-occupation-quarter, after controlling for a firm's overall national demand or local level demand and firm characteristics such as size. This suggests indeed that firms which have a higher share of the local labor market indeed have more power over them. Our results complement, but also extend, a very recent literature that has explored the effects of labor market concentration.

However, beyond labor market concentration, our measure is firm-specific, and appears to explain a variety of firm-level outcomes. In particular, firms with more labor market power hold less cash and have lower market betas. This translates to higher profitability and Tobin's Q. The effect stems largely from high-skill labor in more mobile industries, and for firms that are more labor intensive. Moreover, the effect is weaker when the industry has a higher unionization rate. Finally, to alleviate identification concerns, we interact our labor market power measure with the fractional exposure of a firm's job postings to the passage of non-compete laws as recently documented in Jeffers (2017).

In summary, the cross-sectional analysis suggests that for firms with relatively low market power, these firms afterwards hold less cash. In contrast, it appears the effect is relatively mitigated for firms which have higher levels of market power. This suggests that our measure interacts with meaningful variation in the labor market documented in prior studies to produce the following relationship: market power in the labor market appears to matter more specifically for situations where workers conceivably have more power.

A meaningful question is the extent to which labor market power explains other firm outcomes, particularly the ability of the firm to capture investment opportunities and compete against rivals. For example, firms with high labor market power may differentially behave when there is an increase in growth opportunity in the industry, because these firms can quickly adapt to the growth opportunity by finidng suitable new workers. Using our novel dataset, these are questions we plan to explore in future research.

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Table 1: Sample counts of job postings

This table presents sample counts of job-postings by year. An employer is a unique name observed in our job postings dataset. A public company is a name-matched firm from Compustat. Data from 2008 and 2009 are not available by our data provider.

Panel A: Public				
Year	# Firms	# Jobs (millions)	% Salary reported	Wages
2007	3079	2.81	6.65	65574.09
2010	4089	3.03	5.16	71070.18
2011	4328	3.66	5.08	68244.82
2012	4400	3.9	3.96	71789.84
2013	4773	5.06	3.83	69429.27
2014	4530	6.18	4.03	69183.49
2015	4495	7.59	5.19	69698.37
2016	4146	7.43	5.79	68430.24
Panel B: All				
2007	# Firms	# Jobs (Millions)	% Salary Reported	Wages
2010	14096	13.53	11.97	59294.92
2011	61377	11.70	16.88	61599.73
2012	73615	14.23	17.95	61297.17
2013	62983	14.08	15.16	61111.72
2014	76082	18.46	15.23	60829.31
2015	87388	20.09	15.96	63755.71
2016	120723	26.89	16.43	69946.74

Table 2: Statistics of sample firms versus Compustat Universe

This table presents statistics of all Compustat firms (Panel A) versus firms in our sample (Panel B). The sample years are 2007, 2010-2016. In Compustat variable names, age is the number of years since listing, assets is at, sales is SALE/AT, profitability is NI/AT, leverage is (dlc+dltt)/AT, cash is che/AT, and Tobin's Q is $prcc_f \times csho/at$.

Panel A								
	N	Asset	Tobin's Q	Cash	Debt	Prof	Sale	Age
N	93042	72054	64412	71711	71503	71348	71345	93042
Mean	93042	12367.64	3.75	0.211	0.307	-0.325	0.696	14.54
SD	93042	105364.4	8.206	0.258	0.494	1.108	0.845	14.334
Q5	93042	0.685	0.709	0.002	0	-2.205	0	1
Q25	93042	34.264	1.019	0.03	0.007	-0.13	0.068	4
Q50	93042	335.352	1.403	0.098	0.166	0.008	0.435	10
Q75	93042	2158.292	2.474	0.291	0.386	0.05	0.996	20
Q95	93042	27421.85	14.245	0.854	0.992	0.162	2.318	48
Panel B								
	N	Asset	Tobin's Q	Cash	Debt	Prof	Sale	Age
N	23290	22752	21388	22749	22645	22731	22730	23290
Mean	23290	23554.96	1.916	0.176	0.248	-0.014	0.873	24.359
SD	23290	151175.5	1.269	0.206	0.261	0.282	0.778	17.663
Q5	23290	44.271	0.924	0.005	0	-0.329	0.045	4
Q25	23290	392.314	1.095	0.034	0.048	-0.002	0.318	11
Q50	23290	1678.323	1.46	0.095	0.196	0.028	0.692	19
Q75	23290	6899.547	2.184	0.237	0.367	0.067	1.198	32
Q95	23290	58039.81	4.816	0.653	0.681	0.154	2.373	62

Table 3: Summary statistics of labor market-power proxies

This table presents variations of our main measure of labor market share, a proxy for market power. The baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t,} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. The metro-level measure re-defines the county as an MSA. $LMS^{high}_{i,t,}$ filters out all job postings not having a bachelor's degree or five years of experience as a requirement, whereas $LMS^{low}_{i,t,}$ is the logical complement.

	LMS	LMS^{met}	LMS^{high}	LMS^{low}
Mean	0.009	0.007	0.009	0.006
SD	0.016	0.014	0.018	0.013
Q5	0.001	0	0	0
Q25	0.002	0.001	0.001	0.001
Q50	0.004	0.003	0.003	0.002
Q75	0.01	0.007	0.009	0.006
Q95	0.035	0.027	0.038	0.023

Table 4: Main result on cash holding

This table presents our main baseline result. The hypothesis is that market power in the labor market should allow a firm to operate with more financial flexibility. Our main measure of firm flexibility is cash to assets. The baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t}, = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level.

	$\frac{Cash}{At}$					
LMS	-0.683***				-0.742***	
	t = -3.428				t = -2.993	
$\ln(1 + LMS)$		-0.679***	-0.637***	-0.602***		-0.718***
		t = -3.726	t = -3.601	t = -3.415		t = -3.207
$\ln(At)$	-1.497***	-1.506***	-5.045***	7.130***	11.199***	11.227***
	t = -8.608	t = -8.631	t = -6.918	t = 3.076	t = 3.175	t = 3.183
Age	-0.030**	-0.031**	-0.034**	-0.023*	-0.037**	-0.037**
	t = -2.166	t = -2.190	t = -2.474	t = -1.696	t = -2.287	t = -2.304
$Sales\ Growth$	-0.0001**	-0.0001**	-0.0001*	-4E-05	-1E-05	-1E-05
	t = -1.983	t = -2.001	t = -1.898	t = -1.473	t = -0.392	t = -0.416
$\frac{Debt}{At}$	-15.173***	-15.187***	-14.237***	-14.264***	-14.615***	-14.635***
	t = -7.956	t = -7.960	t = -7.517	t = -7.664	t = -6.066	t = -6.070
$Prof$	-9.039***	-9.047***	-6.707***	-8.446***	-8.356***	-8.380***
	t = -4.899	t = -4.901	t = -3.678	t = -4.769	t = -4.486	t = -4.495
$Sales$	-3.335***	-3.336***	-3.607***	-3.537***	-5.079***	-5.079***
	t = -5.202	t = -5.202	t = -5.496	t = -5.487	t = -8.191	t = -8.188
$Tobin's\ Q$	4.249***	4.245***	4.236***	4.249***	4.109***	4.105***
	t = 16.433	t = 16.409	t = 16.429	t = 16.672	t = 15.055	t = 15.031
$\ln(\#Postings)$	-0.136	-0.146	0.906***	2.196***	3.183***	3.191***
	t = -1.347	t = -1.457	t = 3.113	t = 3.670	t = 3.894	t = 3.904
$\frac{Postings}{National\ Market}$	439.860**	441.504**	644.765***	-145.325	-236.168	-230.04
	t = 2.233	t = 2.250	t = 3.124	t = -0.627	t = -0.881	t = -0.857
Include SIC4/6?	Y	Y	Y	Y	N	N
Size Order?	1	1	2	3	3	3
Obs.	19414	19414	19414	19414	13917	13917
R^2	0.608	0.608	0.612	0.617	0.61	0.61
Adj. R^2	0.54	0.54	0.545	0.55	0.529	0.529

Table 5: Labor market power and other outcome variables

This table presents our main baseline result. The hypothesis is that market power in the labor market should allow a firm to operate with more financial flexibility. Our outcome variables are leverage, univariate market beta, Tobin's Q, and profitability (ni/at). The baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t,} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level.

	$\frac{Debt}{At}$	$\ln\left(\frac{Debt}{At}\right)$	β	$Tobin's\ Q$	$\ln(Q)$	$Prof$
LMS	-0.171	-0.001	-0.031***	0.035**	0.010**	0.031***
	t = -0.719	t = -0.670	t = -2.729	t = 2.375	t = 2.346	t = 3.838
$\ln(1 + LMS)$	1.992***	0.017***	0.118***	-0.01	-0.0001	0.174***
	t = 11.284	t = 11.893	t = 10.849	t = -0.950	t = -0.020	t = 16.295
$\ln(At)$	-0.072***	-0.001***	-0.004***	-0.004***	-0.001***	0.001
	t = -4.050	t = -3.609	t = -4.222	t = -4.154	t = -3.573	t = 1.540
Age	-3E-05	0	-0.00001**	0.00001**	0.00000***	0
	t = -0.863	t = -0.898	t = -2.338	t = 2.498	t = 2.781	t = -0.063
$Sales\ Growth$	-28.828***	-0.246***	0.547***	2.310***	0.656***	-1.089***
	t = -14.527	t = -14.869	t = 5.904	t = 15.742	t = 16.533	t = -8.679
$\frac{Debt}{At}$			0.281***	0.497***	0.158***	-0.974***
			t = 4.483	t = 4.427	t = 4.957	t = -8.040
$Prof$	-17.816***	-0.168***	-0.278***	0.482***	0.141**	
	t = -9.386	t = -9.070	t = -3.815	t = 2.683	t = 2.364	
$Sales$	-3.069***	-0.020***	-0.026	0.221***	0.065***	0.154***
	t = -4.696	t = -3.165	t = -1.045	t = 5.883	t = 5.993	t = 4.880
$Tobin's\ Q$	0.790***	0.009***	0.056***			0.131***
	t = 2.578	t = 2.896	t = 4.901			t = 7.745
$\ln(\#Postings)$	-0.237*	-0.002*	0.008	0.024***	0.008***	-0.005
	t = -1.897	t = -1.729	t = 1.121	t = 3.198	t = 3.615	t = -0.932
$\frac{Postings}{National\ Market}$	-132.56	-1	-60.194***	5.702	1.466	-45.629***
	t = -0.557	t = -0.520	t = -4.098	t = 0.428	t = 0.388	t = -5.052
Include SIC4/6?	Y	Y	Y	Y	N	N
Size Order?	1	1	2	3	3	3
Obs.	19414	19414	19414	19414	19414	19414
R^2	0.511	0.495	0.404	0.459	0.491	0.406
Adj. R^2	0.426	0.407	0.301	0.365	0.403	0.303

Table 6: Labor market power and posted wage rates

This table presents our main result on posted wages. The hypothesis is that market power in the labor market should allow firms to pay lower wages. The baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t}, = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered as indicated.

	ln $(wage)$					
$LMS_{i,t,c}$	-0.012**	-0.012				
	t = -1.978	t = -1.291				
$LMS_{i,t}$			-0.035*		-0.034**	
			t = -1.664		t = -2.086	
$\ln(1 + LMS_{i,t})$				-0.033*		-0.028*
				t = -1.719		t = -1.819
$\ln(CountyPostings)$	0.015***	0.015*	0.011	0.01	0.007*	0.006
	t = 3.077	t = 1.662	t = 1.423	t = 1.335	t = 1.709	t = 1.526
$\ln(PostingsFirm)$	0.010***	0.01	0.023**	0.023**	0.019**	0.018**
	t = 3.766	t = 0.635	t = 2.435	t = 2.413	t = 2.432	t = 2.246
$\ln(\#Skills)$	0.062***	0.062***	0.026	0.026	0.033**	0.032**
	t = 18.328	t = 2.644	t = 1.214	t = 1.219	t = 1.974	t = 1.971
Firm Controls?	Y	Y	Y	Y	Y	Y
County-Quarter?	Y	Y	Y	Y	Y	Y
SOC-Quarter?	Y	Y	Y	Y	Y	Y
Firm FE?	Y	Y	N	N	Y	Y
Cluster?	county	firm	firm	firm	firm	firm
Obs	1098635	1098635	1098635	1098635	1098635	1098635
R^2	0.381	0.381	0.386	0.386	0.517	0.517
Adj. R^2	0.359	0.359	0.355	0.355	0.491	0.491

Table 7: Labor market power and industry capital-labor intensity

In this table, we explore the cross-sectional relation of industry capital-labor intensity and our measure of labor market power. Industry capital-labor intensity is the SIC four digit capital/labor (ppent/emp) ratio equal-weighted across firms in the same year. The baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t,} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level.

	$\frac{Cash}{At}$		$Tobin's\ Q$	
LMS	-0.716***			0.030**
	t = -3.518			t = 2.427
$\ln(1 + LMS)$		-0.697***	0.023**	
		t = -3.760	t = 2.011	
$\frac{K}{L} \times LMS$	0.190**			-0.005
	t = 2.435			t = -1.162
$\frac{K}{L} \times \ln(1 + LMS)$		0.187**	-0.005	
		t = 2.324	t = -1.058	
Obs.	19268	19268	19268	19268
R^2	0.61	0.61	0.459	0.46
Adj. R^2	0.542	0.542	0.365	0.365

Table 8: Labor market power and industry unionization rate

In this table, we explore the cross-sectional relation of industry unionization rate and our measure of labor market power. Industry unionization rate is matched to the SIC4 level. The baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t}, = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level.

	$\frac{Cash}{At}$		$Tobin's\ Q$	
LMS	-2.114***			0.092**
	t = -2.912			t = 2.274
$\ln(1 + LMS)$		-1.895***	0.078**	
		t = -2.730	t = 1.990	
$Union \times LMS$	0.716**			-0.034**
	t = 2.202			t = -2.055
$Union \times \ln(1 + LMS)$		0.592**	-0.029**	
		t = 1.993	t = -1.973	
Obs.	14773	14773	14773	14773
R^2	0.609	0.609	0.411	0.412
Adj. R^2	0.531	0.531	0.294	0.294

Table 9: Decomposing labor market power into high-skill and low-skill labor

Our main measure of labor market power is $LMS_{i,t}^{high}$. The calculation method is explained in section 2.3 and in Table 4. The baseline labor market share measure, $LMS_{i,t}$, is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t,} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. $LMS_{i,t}^{high}$ takes into account the subset the universe of job-postings to only those requiring 5 years of experience or 16 years of schooling (Bachelor's degree). The measure $LMS_{i,t}^{low}$ is similarly defined, but only takes as an input all job postings lacking the requirement of a bachelor's degree or five years experience. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level.

	$\frac{Cash}{At}$		$Tobin's\ Q$		β	
LMS^{high}	-0.346*	-0.738***	0.036***	0.046***	-0.0001***	-0.0002***
	t = -1.789	t = -2.936	t = 2.800	t = 2.751	t = -2.774	t = -3.346
LMS^{low}	-0.333**	-0.039	-0.019	-0.026	5E-05	2E-05
	t = -2.054	t = -0.179	t = -1.530	t = -1.489	t = 0.858	t = 0.376
Include SIC4/6?	Y	N	Y	N	Y	N
Firm Cluster?	Y	Y	Y	Y	Y	Y
Obs.	19414	13917	19414	13917	19414	13917
R^2	0.608	0.605	0.459	0.404	0.404	0.404
Adj. R^2	0.54	0.523	0.365	0.281	0.301	0.281

Table 10: Labor market power and industry-level mobility

In this table, we explore the cross-sectional relation of industry labor mobility and our measure of labor market power. The baseline labor market share measure, $LMS_{i,t}$ is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t,} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level.

	$\frac{Cash}{At}$		$Tobin's\ Q$	
LMS	-0.724***			0.030**
	t = -3.196			t = 2.221
$\ln(1 + LMS)$		-0.691***	0.021	
		t = -3.214	t = 1.643	
$Mobility \times LMS$	-1.226	-1.219	0.005	0.005
	t = -1.172	t = -1.168	t = 0.094	t = 0.100
$Mobility \times \ln(1 + LMS)$	-0.337**			0.017*
	t = -1.992			t = 1.930
Obs.	16607	16607	16607	16607
R^2	0.621	0.621	0.463	0.464
Adj. R^2	0.555	0.555	0.369	0.37

Table 11: Labor market power and non-compete clauses

In this table, we explore the relation of passages of non-compete clauses and our measure of labor market power. The baseline labor market share measure, $LMS_{i,t}$ is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t,} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level.

	$\frac{Cash}{At}$					
CNC	-0.650***	-0.430***	-0.12	-0.024	-0.565***	-0.632***
	t = -4.075	t = -2.673	t = -1.493	t = -0.274	t = -3.686	t = -3.886
$Q_{high} \times CNC$	0.658**		0.167			
	t = 2.015		t = 1.053			
$Q_{low} \times CNC$		-0.502*		-0.278*		
		t = -1.805		t = -1.811		
$LMS \times CNC$					0.163	
					t = 1.051	
$\ln(1 + LMS) \times CNC$						6.471
						t = 0.790
Q_{high}	-0.846**		-0.057			
	t = -2.106		t = -0.246			
Q_{low}		1.350***		0.112		
		t = 3.109		t = 0.427		
LMS					-0.723***	
					t = -3.665	
$\ln(1 + LMS)$						-47.187***
						t = -3.972
Obs.	19405	19405	19405	19405	19405	19405
R^2	0.608	0.608	0.92	0.92	0.608	0.608
Adj. R^2	0.54	0.54	0.88	0.88	0.54	0.54

Online Appendix

Table A.1: Labor market shares and firm-level wages

In this table we aggregate wages to the firm-level, averaged across the year. We then examine the relation between market power and wages. Our measures of wage are listed in-line. is simply the average of the min and max salary for a position in our job postings dataset. is the log-wage adjusted for industry by month and occupation by month fixed effects and its relationship to the log number of skills. In other words, it is the residual of such a regression.The baseline labor market share measure, $LMS_{i,t}$ is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t,} = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects. Standard errors are clustered at the firm level. Relative to prior analyses, missing observations refer to those who have no observations in the firm-year generally as the wages are redacted from a posting.

	Wage Median	Wage Median	Log-Wage Median	Log-Wage Mean	Log-Wage Average Mean	Log-Wage Mean
LMS	-449.836		-0.009			-0.01
	t = -0.619		t = -1.015			t = -1.587
$\ln(1 + LMS)$		-584.31		-0.011	-0.010*	
		t = -0.838		t = -1.328	t = -1.661	
Obs.	12391	12391	12391	12391	12391	12391
R^2	0.257	0.257	0.274	0.278	0.204	0.204
Adj. R^2	0.058	0.058	0.079	0.084	-0.009	-0.009

Table A.2: Labor market shares and firm-level wages

In this table we compare our main measure of market power to firm-level market concentration. The baseline labor market share measure, $LMS_{i,t}$ is calculated as follows. Denote firm i, county c, and time t and the as the sum of all postings by the top 4 posters in a county. Then, a firm's is $LMS_{i,c,t} = \frac{postings_{i,c,t}}{top4_{c,t}}$. The firm-level measure is weighted by postings in the county. Therefore $LMS_{i,t}, = \sum_{c \in counties} \frac{postings_{i,c,t}}{postings_{i,t}} LMS_{i,c,t}$. All specifications include industry-by-year fixed effects clustered at the firm level.

	$\frac{Cash}{At}$			
LMS	-0.478**	-0.618**	-0.587**	-0.750**
	t = -2.098	t = -2.069	t = -2.478	t = -2.385
$HHI \times LMS$	-0.491***	-0.377	-0.859***	-0.769**
	t = -2.902	t = -1.614	t = -3.912	t = -2.488
HHI			0.201***	0.210**
			t = 3.340	t = 2.545
Include SIC 4/6?	Y	N	Y	N
Obs.	19414	13917	19414	13917
R^2	0.608	0.605	0.609	0.605
Adj. R^2	0.54	0.523	0.541	0.524