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Concentration in US labor markets: Evidence from online vacancy data[☆]

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ABSTRACT

Using data on the near-universe of US online job vacancies collected by Burning Glass Technologies in 2016, we calculate labor market concentration using the Herfindahl-Hirschman index (HHI) for each commuting zone by 6-digit SOC occupation. The average market has an HHI of 4,378, or the equivalent of 2.3 recruiting employers. 60% of labor markets are highly concentrated (above 2500 HHI). Highly concentrated markets account for 16% of employment. Labor market concentration is negatively correlated with wages, and there is no relationship between measured concentration and an occupation's skill level. These indicators suggest that employer concentration is a meaningful measure of employer power in labor markets, that there is a high degree of employer power in labor markets, and also that it varies widely across occupations and geography.

1. Introduction

Monopsony power of employers in labor markets is not a new subject for labor economists, but prior work has generally focused on specific occupational markets thought to be specialized and therefore prone to employer power over a captive or semi-captive workforce (e.g. Matsudaira, 2013; Staiger et al., 2010, and Ransom and Sims, 2010), or it has focused specifically on the low-wage labor market in the context of changes to the legislated minimum wage (e.g. Dube et al., 2010). In this article, we quantify the level of labor market concentration across nearly all occupations and for every commuting zone in the US, using the near-universe of online job vacancies for 2016 from Burning Glass Technologies (BGT). Based on findings in this and other work, we argue that concentration measured this way is a useful index of employers' market power.

Calculating concentration in labor markets presupposes a market definition. In order to ascertain a rule of thumb for market definition in the labor context, we perform a hypothetical monopsonist test, analogous to the hypothetical monopolist test used for product market definition in the antitrust literature. The essence of such a test is to ask whether, for a given market definition, significant wage suppression would be profitable for an employer monopsonizing that market. The profitability of wage suppression depends on how many workers will leave in the face of wage suppression, i.e. the labor supply elasticity to the candidate market. In other words, conditional on other parameters of labor demand (firm productivity, output price, etc.), variation in the firm-level labor supply elasticity will generate variation in the monopsonistic wage markdown. Thus, we can make use of estimates of the labor supply elasticity corresponding to various market definitions to determine the right definition for our concentration calculations. Ultimately, we utilize as our main market definition a commuting zone-by 6-digit SOC occupation-by quarter market definition. We also present results for alternative market definitions.

The relationship between market definition, labor supply elasticity, and measured concentration of employers suggests that there is more than one way to measure employer market power. Azar et al. (2019b) show that higher market concentration is correlated with lower firm-specific labor supply elasticity, which is consistent with a theory of oligopsonistic labor markets in which employers compete for workers a la Cournot. It is intuitive that markets with fewer employers would result in fewer outside options for existing workers, and hence greater wage-setting power for incumbent firms. While in some models, firm-specific labor supply elasticity may be a more primitive parameter and market concentration of employers an equilibrium outcome, their close association in the data, in addition to the fact that concentration may be more readily measurable, creates a justification for both measuring concentration and using it as an index of market power.

Using the vacancy data from BGT, we calculate Herfindahl Hirschman Indices (HHIs) for labor markets at the occupation (6-digit SOC), commuting zone, and quarterly level. The average market has an HHI of 4378, which is the equivalent of 2.3 recruiting firms with equal

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shares of the total vacancy pool. 60% of markets have concentration greater than 2500. Note that a market with four firms and equal market shares has an HHI of 2,500, so an HHI of 2500 is the equivalent of 4 recruiting firms with equal shares of the total vacancy pool. Another 11% of markets have an HHI between 1500 and 2,500. In antitrust law, a market above 2500 HHI is highly concentrated and it is moderately concentrated between 1500 and 2500 HHI (Department of Justice / Federal Trade Commission 2010 horizontal merger guidelines). Under that definition, 60% of US markets are thus highly concentrated.

When we weight markets by BLS total employment, we find that 16 percent of workers work in highly concentrated labor markets, and a further 7 percent work in moderately concentrated markets. Concentration is lower in large commuting zones, which explains why weighting by employment lowers the prevalence of high concentration.

We also calculate concentration for a number of alternative market definitions in terms of occupation, location, and time. According to several plausible alternative market definitions, we find that at least 40% of markets are highly concentrated. We then perform several descriptive regressions of measured concentration on wages (using both BGT and Bureau of Labor Statistics (BLS) Occupational Employment Statistics data). We show a robust negative association between concentration and wages, using both occupation and commuting zone fixed effects and controlling for the demand state of the labor market. The negative association between concentration and wages is a sign that concentration is at least an indicator of employer market power.

Finally, we show that there is no robust relationship between concentration and several measures of occupational skill, signifying that labor markets are not more or less concentrated (given our market definition) for lower- or higher-skill jobs. From this work, at least, there's no reason to believe that lower skill workers are any less subject to employers' monopsony power, or vice versa.

Our measure of concentration is distinct from the industry concentration measures used by Autor et al. (2020), Barkai (2019), and other work purporting to show declining competition in the macroeconomy and sector-by-sector. Our measure is based on concentration in the labor market rather than concentration in the product market, and we make no claim about its long-term time trend given the available data. Our contribution is the first economy-wide measure of labor market concentration to have been made in many decades.[1]

The papers that come closest to our approach include Azar et al. (2020), Benmelech et al. (2020), Qiu and Sojourner (2019), and Rinz (2018). Azar et al. (2020) examine the impact of concentration on wages but rely on only 17 occupations from one single job board, CareerBuilder.com. Due to these data limitations, that paper could not discuss and measure the sensitivity of concentration to alternative market definitions, or assess the overall level of concentration in the US. Benmelech et al. (2020) use Census data for manufacturing industries to measure employment concentration (as opposed to vacancy concentration) and its negative effect on wages. Rinz (2018) calculates labor market concentration by commuting zone and industry for the whole economy and investigates its impact on wage inequality. Benmelech et al. (2020) and Rinz (2018) focus on industries for defining labor markets, whereas we use six-digit SOC occupations.[2]

In contrast to Benmelech et al. (2020), Qiu and Sojourner (2019) and Rinz (2018), we measure concentration using job openings rather than employment because we view vacancies as a better gauge of how likely searching workers (whether employed or unemployed) are to receive a job offer. Recent studies show that workers remain in jobs for longer.[3] The corollary is that jobs are vacated less frequently, and so the concentration of employment may be a less relevant gauge of available work and employer market power than is the concentration of vacancies among the relatively few firms who are likely to be hiring at any given time. We further discuss this issue in Section 2.1. In theory, the wages for new hires are likely to be more flexible and sensitive to market conditions, be they macroeconomic fluctuations or changes in the degree of employer power, and so they offer a more variable indicator of the outcome of interest for tests of employer power. However, if vacancy-based concentration is a measure of employer power, it should also affect the wages of currently-employed workers. We use earnings from the Occupational Employment Statistics and show that our vacancy-based measure of concentration has essentially the same effect on the earnings of all workers as on the earnings posted by vacancies on BGT.

The previously-mentioned papers estimating a relationship between labor market concentration and wages or earnings may all suffer from identification problems (see Berry et al., 2019), although Benmelech et al. (2020) are able to control for employer characteristics that are usually considered to be the threats to identification in concentration-outcome regressions using market-level variation. But two recent papers, Arnold (2019) and Prager and Schmitt (2019), use observed mergers as plausibly exogenous variation in concentration unrelated to firm-specific characteristics or market demand parameters to identify a wage effect. Arnold (2019) does so for what is essentially the universe of mergers in the Longitudinal Business Database, while Prager and Schmitt (2019) focus on hospital mergers and workers in occupations employed by hospitals. Both find a significant negative effect of merger-induced concentration on wages, showing that increases in concentration are relevant to merger assessment, as discussed by Marinescu and Hovenkamp (2019).

Section 2 describes the Burning Glass data, Section 3 addresses market definition for labor markets, and Section 4 gives our estimates of labor market concentration. Section 4.1 correlates our labor market concentration estimates with vacancy- and market-level wages. Section 4.2 relates those concentration estimates to other occupation-level variables, to ascertain whether employer market power differs systematically across observable characteristics of occupations. Section 5 places our results in the larger debate over inter-firm inequality and employer power in labor markets, and Section 6 concludes.

2. Data

We use data from Burning Glass Technologies (BGT). The company collects online job postings from about 40,000 websites, which captures the near-universe of online US job vacancies. And over the period of time in which BGT has been collecting this data, online job postings account for an increasing fraction of overall job posting and of hiring in the US labor market. We confine attention to the calendar year 2016, since this is the most recent complete year of data we have, and the BGT data is likely to be most representative of both online and overall vacancy-posting as more recruiting and hiring shifts online.[4]

Importantly, BGT data is fairly similar in terms of industry composition when compared to all vacancies recorded in the Job Openings and Labor Turnover Survey (JOLTS), which is nationally representative of employers. Furthermore, the occupational distribution in BGT data

[1] The last, to our knowledge, is Bunting (1962); see review of literature by Boal and Ransom (1997).

[2] The other thing that Benmelech et al. (2020) and Qiu and Sojourner (2019) are able to do that is beyond the scope of the other studies of labor market concentration, is control for the degree of collective bargaining or unionization in labor markets. They find that those institutions for worker representation mitigate the negative impact of employer concentration, suggesting that employer market power can be countered by worker power. In Appendix D, we control for measures of unionization at the occupation level, but econometrically this is no different than occupation fixed effects and cannot speak to the role of collective bargaining in particular labor markets, using the market definition relied on in this paper.

[3] See Haltiwanger et al. (2018), Molloy et al. (2016), and Hyatt and Spletzer (2016)

[4] Average concentration levels in 2007–2015 are comparable to average concentration levels in 2016.

is similar to the one found in the Occupational Employment Statistics (Hershbein and Kahn, 2018).

To understand the share of job openings captured by BGT, it is important to note BGT only measures new postings (a given posting appears only on the first month it is recorded) while JOLTS measures active postings (the same posting can appear in two or more consecutive months if time to fill is more than 30 days). Help Wanted Online (HWOL) measures both. Therefore, the number of postings on BGT can be inflated using the new jobs to active jobs ratio in HWOL, i.e. the same method used in Carnevale et al. (2014). Based on this calculation, BGT shows that the share of job openings online as captured by BGT is roughly 85% of the job openings in JOLTS in 2016. The jobs that are not online now are usually in small businesses (the classic example being the "help wanted" sign in the restaurant window) and union hiring halls. Overall, however, research shows the online job market has consistently expanded over the last few years.

Hershbein and Kahn (2018) show some evidence that the BGT vacancies have become closer to benchmark employment by occupation in CPS and OES over time, as the BGT dataset has become relatively less dominated by hiring into computational, mathematical, and financial occupations. This is most likely because online hiring has expanded steadily out of the sectors where it originated to become more representative of the labor market as a whole. Our analysis of the occupation-level characteristics of the hiring data shows substantial coverage of low-skilled and low-wage occupations.

The data is cleaned by Burning Glass to remove vacancy duplicates and extract key characteristics for each vacancy. So vacancies posted on multiple sites are represented only once. We do not observe whether vacancies are filled or unfilled, but if the same vacancy is posted multiple times due to remaining unfilled, those multiple postings are collapsed.

Of interest to our work are the location of the vacancy (county), name of the employer, and the occupation. The employer name is how we define different firms for the purpose of computing market concentration. The name of the employer is normalized by BGT so that similar employer names are grouped together into a single employer: for example, "Bausch and Lomb", "Bausch Lomb", and "Bausch & Lomb" would be grouped together. Still, 35.9% of employer names are missing, partly due to staffing companies not disclosing on whose behalf they are posting a given job. To calculate concentration, we assume that all the missing employer names are different from one another and from postings by identified firms, thus providing a lower bound for labor market concentration.

The BGT dataset contains many variables describing the occupation of each vacancy. These include the SOC code, the standardized job title, and the BGT occupation. The standardized job title is based on the full text job title of the job vacancy: the full text job title is cleaned and similar job titles are grouped together. The BGT occupation starts with the SOC code, and either consolidates SOC codes or divides them into several categories based on the similarity of skills, education and knowledge requirements.

We drop internships and data with missing SOC or commuting zones, which represents 5.2% of the initial sample. We are left with a sample of 22,682,265 observations.

For our benchmark analysis, we keep 200 occupations, which represent 90% of vacancy postings in the BGT dataset. We trim away very small occupations because they may be defined too narrowly. We note that this choice results in lower HHI than if we had included all occupations. The total number of markets (6-digit SOC occupation by commuting zone) we consider in our main analysis is 117,369.

Our main summary statistics on HHI treat each cell (commuting zone by 6-digit SOC by quarter) as an observation. But we also want to understand how the summary statistics change when we weight by employment in each of these markets. When we report HHI weighted by employment, we include every occupation in the data, since small and possibly ill-defined occupations will not be overly influential after weighting by employment. To analyze HHI weighted by employment, we use the May 2016 Metropolitan and Nonmetropolitan Area Occupational Employment and Wage estimates from the Bureau of Labor Statistics (BLS). The BLS data is only available at the CBSA level, and not at the commuting zone level. To get commuting zone employment, we first estimate BLS county-level employment: we use county population shares within a CBSA and multiply these shares with the BLS employment by 6-digit SOC at the CBSA level. Finally, to get commuting zone 6-digit SOC employment numbers, we aggregate the 6-digit SOC employment numbers across the counties that form a commuting zone.

For the correlations reported in Section 4.1, we use both the posted BGT annual salary (only available for a subset, 16%, of vacancies), as well as the OES hourly wage and annual salary data, which is available at the SOC-6 by metropolitan statistical area (MSA) level. For each BGT vacancy, we match to OES wage and salary data using the commuting zone and MSA, so those variables are observed at (approximately) the market level, rather than the vacancy level. However, that data is also available only for a subset of vacancies. Not all vacancies are posted by employers located in an MSA, since unlike commuting zones, MSAs cover only urban areas. For all data sources, we use only 2016 data; the aim is to provide a (comprehensive, economy-wide) snapshot of concentration at a point in time.

2.1. Vacancies and hiring

We focus on vacancy-posting as a measure of firm-specific labor demand, and on the concentration of vacancy-posting at particular firms within a labor market as a measure of the concentration of labor demand in a market. This naturally raises questions about what drives vacancy-posting as an economic behavior, and additionally, whether concentration of vacancy-posting is a good metric for the underlying economic characteristic we seek to measure: the market power of employers in a labor market.

Davis et al. (2013) show the vacancy-posting is extremely variable in the cross section of establishments, and that it is positively correlated with establishment-level employment expansion.[5] But at the same time, firms have other margins at their disposal for increasing their size: they can increase their recruiting intensity, reduce the stringency of their screen for prospective employees, or offer a higher wage to increase the yield of a given vacancy. Those authors show that such margins are likely at play, given that vacancy yield is more strongly positively correlated with establishment-level employment expansion than is vacancy-posting per se.

Larger establishments have a higher vacancy-posting rate but lower vacancy yield than smaller establishments, suggesting that smaller firms expand faster and lending some mild stability to the firm size distribution.

Those authors don't consider employer market power to be a factor in vacancy-posting (or in other hiring and recruiting-related decisions), but it may be useful to consider what their findings on vacancies and hiring would imply for a dataset of job vacancies used to analyze market concentration and, potentially, employer market power. Observed vacancies are disproportionately generated by growing firms, relative to the distribution of employment across firms. But vacancies are less weighted toward growing firms than is hiring. Workers seeking employment (or, at the very least, a job offer) are more likely to end up at a growing firm, conditional on firm size. That means that *more hiring* is going on at a subset of firms relative to the set of firms posting vacancies (i.e., those firms that are expanding and using other unseen margins to increase their vacancy yield), in which case estimates of the concentration of vacancies understates the concentration of hiring.

[5] Within a market defined by occupation and geography, we do not distinguish between establishment- and firm-level vacancies, but firms hiring in more than one market (whether or not that's because they have distinct establishments in each market) are counted separately in concentration calculations.

On the other hand, Davis et al. (2013) do report a significant number of hires taking place in establishments which did not have any (observed) posted vacancies in the month prior, at least according to JOLTS. This may be one advantage of an administrative dataset that cumulates all (online) vacancies over time, as opposed to a survey conducted at discrete points in time. But there may be other "hidden" labor demand coming from non-posting employers, but nonetheless observed by workers themselves. In that case, measures of vacancy concentration might over-estimate the degree of hiring concentration.

Using data from France, Marinescu et al. (2019) show that hires-based and employment-based concentration measures are highly correlated, and that employment-based concentration is systematically lower. That is consistent with what Davis et al. (2013)'s findings would suggest about concentration for the United States, though without any data on vacancies per se.

3. Labor market definition

3.1. Herfindahl-Hirschman index

Our baseline measure of concentration in a labor market is the Herfindahl-Hirschman Index (HHI) calculated based on the share of vacancies of all the firms that post vacancies in that market. The HHI is directly related to wages in the Cournot model of oligopsonistic competition. An increase in HHI leads to a proportional increase in the gap between the marginal productivity of labor and wages, i.e. Pigou's rate of exploitation or the wage markdown (Boal and Ransom, 1997).

The formula for the HHI in market m and time t is

$$\mathrm{HHI}_{m,t} = \sum_{j=1}^{J} s_{j,m,t}^2 \tag{3.1}$$

where $s_{j,m}$ is the market share of firm j in market m expressed as a number between 0 and 100. The market share of a firm in a given market and time is defined as the sum of vacancies posted by a given firm in a given market and time divided by total vacancies posted in that market and time. The inverse of the HHI multiplied by 10,000, 10,000/HHI, gives the "equivalent" number of firms in the market, or the number of firms that would result in such an HHI if each had the same share of the market. When reporting average HHI, we first take the average over time t for each market m. A key question is how the labor market should be defined.

3.2. Frictions to worker mobility across markets

The economic literature shows that there are substantial frictions associated with transitioning between labor markets, however defined (Artuc and McLaren, 2015; Artuç et al., 2010; Dix-Carneiro, 2014, and Traiberman, 2019, to name several). Marinescu and Rathelot (2018) (and Manning and Petrongolo, 2017 for the UK) find that job search behavior is quite local, implying that geographic labor markets are also narrowly defined.

No work, to our knowledge, attempts to define labor markets in the education space. Macaluso (2019) defines the concept of "skill remoteness" on the supply and demand sides of a labor market and finds that workers whose skills are further away from the available jobs in their local labor market (defined by city and occupation) are more likely to either move or exit the labor force in response to a layoff. Hershbein and Macaluso (2018) and Modestino et al. (2016) use the same dataset we employ in this paper to characterize the skill distribution of job vacancies as changing in response to the severity of local labor market recessions. But the extent to which workers confine their job searches to an education- or skills-delimited segment of available jobs has not yet been systematically explored (but see some evidence on search across occupations in Marinescu and Rathelot (2018)).

It is important to note that monopsony and market power may render observed transition rates endogenous. For example, workers displaced from their job in a local labor market may be more likely to transition to an unconcentrated than a concentrated labor market.

Recently, Schubert et al. (2020) have shown that workers in different occupations and geographies have access to vastly different outside options, interpreted as job opportunities in occupations other than the one in which they currently work. Thus, delimiting labor markets at the SOC-6 occupation level obscures heterogeneity between workers who work in that occupation in different locations. The implication of that finding is that for purposes of measuring concentration, and potentially of market power, each worker may be operating in his or her own effective market, and an occupation-based market definition may obscure heterogeneity in market power that matters a lot in setting wages. This is a more empirically-grounded interpretation of an idea contained in Naidu et al. (2018) that since labor markets are two-sided, the fact that both "sides" have to choose the other makes market definition a trickier object than in more classical contexts.

Based on this literature, it is clear that labor markets are relatively narrow, but how exactly a labor market should be defined remains unclear.

Conceptually, to define a market, we have to strike a balance between too narrow a definition and too broad a definition. If the definition is too narrow, there are plenty of opportunities outside the market. If the definition is too broad, it overestimates the similarity of jobs within the market, and therefore overestimates the opportunities available within a market. Given that workers do transition occasionally across essentially any market, it is not reasonable to define a market by the requirement that no worker ever goes outside the boundaries of this market. Instead, a market can conceptually be defined by a threshold level of across-market transitions such that if transitions are above this threshold, the market is too narrow, and if they are below this threshold the market is too broad. In the following sections, we explain how we arrive at a market definition using just such a threshold concept.

3.3. Market definition: Time and geography

For our baseline analysis, we calculate HHI at the quarterly level, since the median duration of unemployment is about 10 weeks in 2016 (BLS, 2016).[6] We consider for our market share calculations all vacancies that occur within a given quarter. We will also show results for other time aggregations.

We use commuting zones (CZs) to define geographic labor markets. Commuting zones are geographic area definitions based on clusters of counties that were developed by the United States Department of Agriculture (USDA) using data from the 2000 Census on commuting patterns across counties to capture local economies and local labor markets in a way that is more economically meaningful than county boundaries. According to the USDA documentation, "commuting zones were developed without regard to a minimum population threshold and are intended to be a spatial measure of the local labor market." Marinescu and Rathelot (2018) also show that 81% of applications on CareerBuilder.com are within the commuting zone, with the probability of submitting an application strongly declining in the distance between the applicant's and the job's zip code. We also conduct robustness checks using other geographical areas for our market definition instead of commuting zones.

3.4. Market definition: Occupation

To organize the discussion of market definition in terms of occupation, we apply the "hypothetical monopsonist test" (HMT). The HMT is analogous to the hypothetical monopolist test that is commonly used for product market definition. The idea of the hypothetical monopolist test is to define the smallest market for which a hypothetical monopolist that controlled that market would find it profitable to implement a

[6] While most job transitions are employment-to-employment, no equivalent concept of search duration exists for such transitions.

"small significant non-transitory increase in price" (SSNIP). The idea is that if the market were defined more narrowly, a monopolist implementing such a price increase would lose sufficient demand as to make that price increase unprofitable. In other words, that lost demand would be to other sellers which ought to be included within the market. Harris and Simons (1989) established that methodology as "critical loss analysis," with the associated critical elasticity the demand elasticity with respect to a candidate market for which a SSNIP is profitable.

Analogously, the hypothetical monopsonist test would suggest as the relevant market the smallest labor market for which a hypothetical monopsonist that controlled that labor market would find profitable to implement "small significant non-transitory reduction in wages" (SSNRW).

Consider a simple model of monopsony, with a constant value of marginal product of labor given by a and a wage w which depends on the employment level of the monopsonist L. The profits of the monopsonist are

$$\pi(L) = (a - w)L.$$

If the monopsonist changes wages by Δw, and this generates a change in labor supply ΔL, the change in profits is

$$\Delta\pi = \Delta L \times (a - w - \Delta w) - \Delta w \times L.$$

Thus, the SSNRW is profitable for the monopsonist if and only if

$$\Delta L \times (a - w - \Delta w) > \Delta w \times L.$$

Dividing on both sides by wL, we obtain

$$\frac{\Delta L}{L} \times \left(\underbrace{\frac{a-w}{w}}_{\text{Markdown}\,\mu} - \frac{\Delta w}{w} \right) > \frac{\Delta w}{w}.$$

Rearranging terms (and taking into account that the change in wage is negative, which changes the direction of the inequality):

$$\frac{\Delta L/L}{\Delta w/w} < \frac{1}{\mu - \Delta w/w}.$$

Since the left-hand side is approximately the elasticity of labor supply, which we denote η, we have that the critical elasticity (see Harris and Simons (1989) for the corresponding concept in the product market) for the wage reduction to increase profits is:

$$\eta \approx \frac{1}{\mu - \Delta w/w}.$$

The antitrust practice typically considers a 5% increase in price (for at least a year) as the SSNIP. Therefore, we will consider a 5% "small significant non-transitory reduction in wages" (SSNRW). The market is too broad if the actual labor supply elasticity to that candidate market is less than the critical elasticity. For example, if the markdown μ of wages relative to the value of the marginal product of labor is 45% and the wage reduction is 5%, then the critical elasticity is $1/(.45+.05)=2$, implying that if the market-level elasticity of labor supply corresponding to the proposed market definition is less than 2, the market definition is too broad, and it should be defined more narrowly. On the other hand, if the market-level elasticity of labor supply is higher than 2, the market is too narrow, and it should be defined more broadly.

Empirically, we have estimates of the labor supply elasticity to the individual firm, which should be larger than the labor supply elasticity to an entire market η. Estimates of the elasticity of labor supply to the individual firm typically range between 0.1 and 4, with most estimates being below 2 (Manning, 2011). Even in online labor markets like Amazon Mechanical Turk, where frictions should be minimal, the labor supply elasticity is only 0.1 (Dube et al. (2020)). Therefore the elasticity of labor supply to the market is typically below 2.[7] This implies that, unless we believe that the markdown is above 45%, markets with an elasticity below 2 are well defined according to the SSNRW.

The low elasticity of labor supply to the individual firms found in the literature suggests that even the narrowest definition of a labor market can pass the test: most *individual* firms already have very low elasticities of labor supply, and so each firm may be seen as a market of its own. For the purpose of the present paper, we take a less radical approach. We want to determine whether our baseline choice of the 6-digit SOC occupation is a reasonable market definition. Using online job board data from CareerBuilder.com, Marinescu and Wolthoff (2019) show that, within a 6-digit SOC, the elasticity of applications with respect to wages is *negative*. Therefore, the 6-digit SOC is too broad of a market according to the SSNRW.

When narrowing the market definition to look at job titles, as opposed to 6-digit occupations, the elasticity of applications with respect to wages is positive and equal to 0.77 (Marinescu and Wolthoff, 2019). The elasticity of applications with respect to wages, when interpreted as a recruitment elasticity, is roughly equal to half the elasticity of labor supply. Therefore, the elasticity of labor supply for job titles is around 1.5, which is below the critical elasticity of 2 implied by a 45% markdown on wages. This analysis suggests that, according to the SSNRW test, a job title is a legitimate labor market for the purpose of antitrust analysis.

Ultimately, we choose to define the line of work as a 6-digit SOC as the baseline. This choice is conservative in that the 6-digit SOC is likely too broad, and therefore labor market concentration will tend to be underestimated. We report concentration estimates for many alternative market definitions in each of these dimensions.

4. Labor market concentration estimates and analysis

We compute vacancy shares by employer using the employer name as the employer ID.[8] Table 1 shows summary statistics for labor market concentration for alternative market definitions. In our baseline market definition as a SOC-6 occupation by commuting zone by quarter, the average HHI is 4378. 60% of markets are highly concentrated, i.e. above 2,500. To put the average HHI into perspective, one firm with 50% of vacancies, another one with 35% of vacancies, and a third with 15% yield an HHI of 3,950. On average, the number of firms is 12.6, which seems high,[9] but the average HHI of 4378 indicates that most vacancies are posted by just a few firms. In fact, the average HHI implies that the equivalent number of firms recruiting is just 2.3 on average. Furthermore, note that the 25th percentile for the number of firms is 1.5, i.e. in a quarter of the markets there are fewer than two equivalent firms recruiting on average.

Looking at percentiles of the HHI beyond the mean, the 75th percentile of HHI is 7279. Again, to place this 7279 number in perspective, a market with one firm having 80% of vacancies and another one having 20% yields an HHI of 6,800.

While 60% of markets are highly concentrated, another 11% of markets are moderately concentrated, i.e. have an HHI between 1500 and 2,500. Only 29% of markets have low concentration (below 1500 HHI).

To complement these national statistics, Fig. 1 shows a map of all the commuting zones in the United States color-coded by the average HHI, based on vacancy shares. Commuting zones around large cities have lower levels of labor market concentration than smaller cities or

[7] See also Azar et al. (2019a) for a model that estimates firm- and market-level labor supply elasticities separately.

[8] If two employers in the same market have different names but are in fact under the same management for the purposes of hiring and wage-setting, our procedure would under-estimate both the level of "effective concentration" and, most likely, the concentration-earnings relationship. This is likely going on in the data, e.g. with franchising.

[9] The maximum number of firms, at 1983.8, is the average number of firms across the four quarters of 2016 for "Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products" in the New York commuting zone. Overall, there are 29 markets with more than 1000 firms.

Table 1
Summary statistics for labor market concentration, for the baseline and alternative market definitions. This table shows summary statistics for labor market Herfindahl-Hirschman Index (HHI) under various market definitions, for the year 2016 using data from Burning Glass Technologies (BGT). The baseline is calculated using commuting zones for the geographic market definition, 6-digit SOC codes for the occupational market definition, aggregating the data at the quarterly level (and then averaging over quarters for a given CZ $\times$ SOC). In the alternative definitions, the calculation is done by changing the baseline along one dimension (occupation, geography, time horizon). Except for the HHI weighted by employment, concentration is calculated over the top occupations (top 200 ranked based on the number of vacancies in the case of 6-digit SOC, representing 90% of vacancies; or BGT occupation definitions, and top 60 in the case of 3-digit SOC (representing 98% of vacancies) or BGT broader occupation group definitions) over the period 2016Q1–2016Q4.

	Mean	Min	Max	25th Pctile.	75th Pctile.	Fraction Moderately Concentrated	Fraction Highly Concentrated
Baseline market definition:							
Number of Firms (Unweighted)	12.6	1.0	1983.8	1.5	8.3		
HHI (Unweighted)	4378	4	10,000	1232	7279	0.11	0.60
HHI (Weighted by BLS Employment)	1361	4	10,000	176	1346	0.07	0.16
Alternative occupational definition:							
HHI (By Job Title)	5892	11	10,000	2896	10,000	0.08	0.78
HHI (By BGT Occupation)	4384	4	10,000	1230	7333	0.11	0.60
HHI (By BGT Broader Occupation Group)	2943	6	10,000	568	4744	0.12	0.40
HHI (By 3-digit SOC)	2956	10	10,000	570	4774	0.12	0.40
HHI (By 2-digit SOC)	2029	9	10,000	325	2638	0.10	0.26
Alternative geographical definition:							
HHI (By County)	6029	5	10,000	2971	10,000	0.08	0.78
HHI (By State)	859	2	10,000	141	769	0.05	0.07
Alternative time aggregation:							
HHI (Monthly)	5926	9	10,000	3043	8750	0.07	0.78
HHI (Semesterly)	3466	2	10,000	788	5278	0.14	0.47

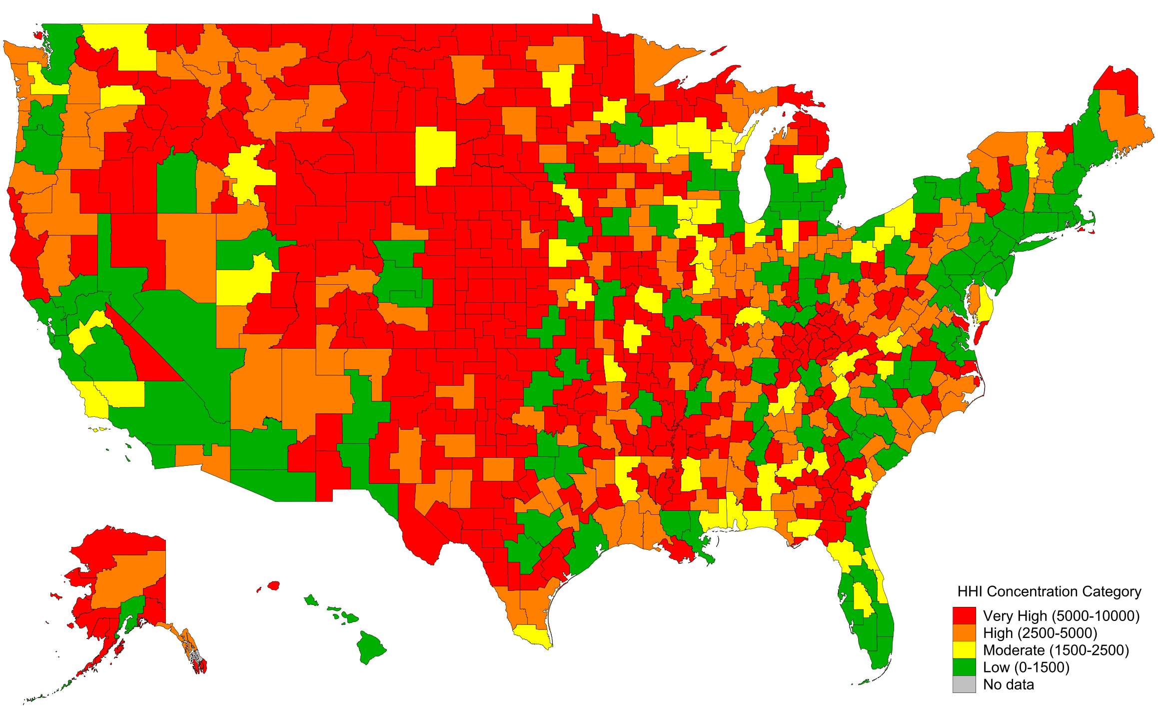
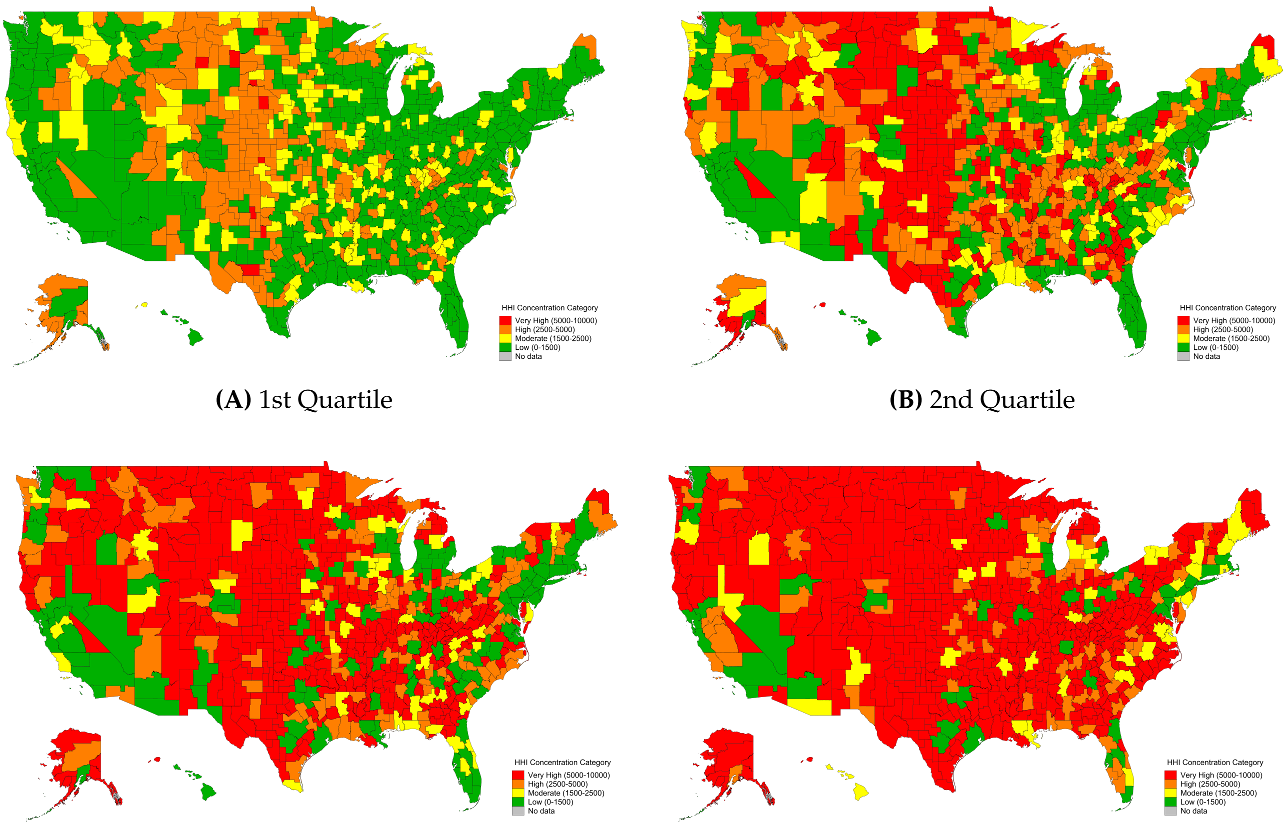


Fig. 1. Average HHI by commuting zone, based on vacancy shares. This figure shows the average of the Herfindahl-Hirschman Index by commuting zone code for the top 200 SOC-6 occupations (ranked based on the number of vacancies) over the period 2016Q1–2016Q4 in the Burning Glass Technologies dataset. The categories we use for HHI concentration levels are: "Low": HHI between 0 and 1500; "Moderate": HHI between 1500 and 2500; "High": HHI between 2500 and 5000; "Very High": HHI between 5000 and 10000. These categories correspond to the DOJ/FTC guidelines, except that we add the additional distinction between high and very high concentration levels around the 5000 HHI threshold. Market shares are defined as the sum of vacancies by a given firm in a given market (6-digit SOC by commuting zone) and year-quarter divided by total vacancies posted in that market and year-quarter.



(A) 1st Quartile

(B) 2nd Quartile

(C) 3rd Quartile

(D) 4th Quartile

Fig. 2. Map of average HHI by commuting zone, by quartile of HHI. This figure shows averages by quartile of the Herfindahl-Hirschman Index by commuting zone for the top 200 SOC-6 occupations (ranked based on the total number of national-level vacancies) over the period 2016Q1–2016Q4 in the Burning Glass Technologies dataset. Within each commuting zone (CZ), we order the 200 occupations by concentration to form four quartiles. The map for the first quartile represents the average concentration across 2016Q1–2016Q4 among first quartile occupations for each CZ, and similarly for other quartiles. The categories we use for HHI concentration levels are: "Low": HHI between 0 and 1500; "Moderate": HHI between 1500 and 2500; "High": HHI between 2500 and 5000; "Very High": HHI between 5000 and 10000. These categories correspond to the DOJ/FTC guidelines, except that we add the additional distinction between high and very high concentration levels around the 5000 HHI threshold. Market shares are defined as the sum of vacancies by a given firm in a given market and year-quarter divided by total vacancies posted in that market (6-digit SOC by commuting zone) and year-quarter.

rural areas. Fig. 3 illustrates the relationship between commuting zone population and concentration: we see that the relationship is roughly linear in logs, with commuting zones with larger populations having lower concentration.

This suggests a new explanation for the city-wage premium (Baum-Snow and Pavan, 2012; Yankow, 2006)): cities, and especially large cities, tend to have less concentrated labor markets than rural areas.[10] The literature on geographic wage differentials has tended to emphasize selection of higher-productivity workers into local economies that offer better opportunities for job-switching and upward career progression, while at the same time mitigating the higher wages on offer with higher cost of living. Geographic differences in firm-level labor market power may play a role, but on the other hand, worker selection effects might confound any relationship between observed concentration and the ostensible effects of market power, such as lower wages. While this paper by itself does not attempt to distinguish between the two, Azar et al. (2020) find significant within-market effects of varying concentration on labor market outcomes.

In Fig. 2, we show the quartiles of HHI across the US, and reveal substantial heterogeneity in concentration across occupations even within a commuting zone. For each commuting zone, we define quartiles of concentration of the top 200 6-digit SOCs: the first quartile contains the 25% least concentrated occupations on average over 2016 Q1-Q4 in that commuting zone, the second quartile contains the next 25% least concentrated occupations in the commuting zone, etc. Therefore, the quartiles can contain different occupations in each commuting zone depending on the local level of the HHI. The map is color coded according to the average level of the HHI in each quartile for each commuting zone. There are few commuting zones that have highly concentrated occupations in the first quartile of concentration. Most of the commuting zones with highly concentrated occupations in the first quartile are in the middle of the country at the west end of the Great Plains. At the other extreme, occupations in the fourth quartile of concentration are extremely highly concentrated with an HHI above 5000 in almost all (86%) of the US commuting zones. Therefore, for much of the country, the least concentrated 25% of occupations have low concentration, while the most concentrated 25% of occupations have extremely high concentration.

To further explore the variation in HHI by occupation, we report the average HHI in the largest 30 occupations in Fig. 4. There is substantial heterogeneity across the most frequent occupations: over a third are highly concentrated, about one third are moderately concentrated and less than one third have low concentration. The most concentrated frequent occupation is marketing managers and the least concentrated frequent occupation is registered nurses.

[10] Manning (2010) shows evidence on plant size that is consistent with lower monopsony power in cities.

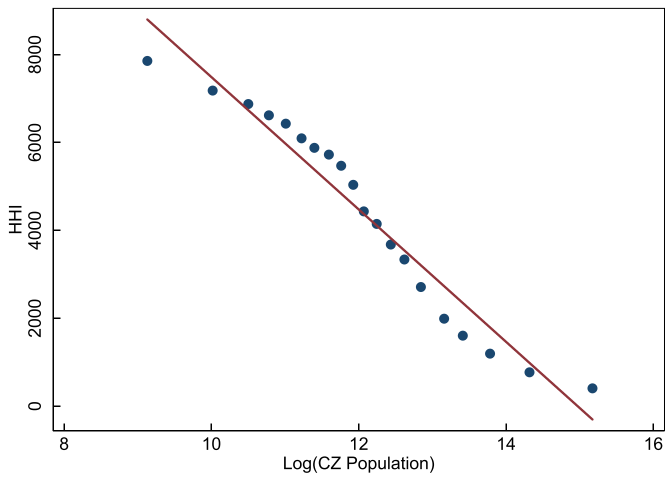


Fig. 3. Binned scatter of HHI and Population. This figure shows a binned scatter of the Herfindahl-Hirschman Index by commuting zone for the top 200 SOC-6 occupations (ranked based on the number of vacancies) over the period 2016Q1–2016Q4 in the Burning Glass Technologies dataset, and log of population in the corresponding commuting zone in 2016 (based on Census data).

The majority of labor markets are highly concentrated according to our baseline definition of concentration. At the same time, it is also interesting to examine the extent to which US workers as a whole face high concentration. When weighting each labor market by the number of employed workers (using OES employment tabulations), we find that HHI is 1361 on average, implying an equivalent number of recruiting firms of 7.3. This relatively low level of concentration is due to the fact that, as mentioned above, concentration is lower in commuting zones with higher population. However, even after taking into account the unequal distribution of employment across markets, we find that 16% of employment is in SOC-6 by CZ by quarter cells that have high levels of concentration. Another 7% of employment is in markets that are moderately concentrated. Overall, 23% of employment is in moderately or highly concentrated markets, and these markets represent 71% of all labor markets.

So far, we have discussed variation in concentration while holding the market definition in terms of 6-digit SOC by commuting zone by quarter fixed. We now examine how concentration changes when we vary the definition of each one of these elements. Starting with occupation, we report HHI for four alternative definitions. First, when using standardized job titles to define an occupational labor market, we find that the average concentration is higher than in the benchmark, at 5892 (Table 1). This higher concentration was to be expected, since job titles are more granular than 6-digit SOCs. When using job titles as the definition of an occupation, 78% of markets are highly concentrated.

As mentioned above, there are reasons to think that the job title may be the most appropriate definition of the labor market. Marinescu and Wolthoff (2019) find that within labor markets defined at the SOC-6 level, there is a negative correlation between the posted wage and the application rate, but looking within labor markets defined by job title, that correlation is positive, as search theory would predict. Using the lens of a search model, Marinescu and Wolthoff (2019) interpret the negative correlation between applications and wages as an indication of significant skill heterogeneity among workers within a SOC-6. In or-

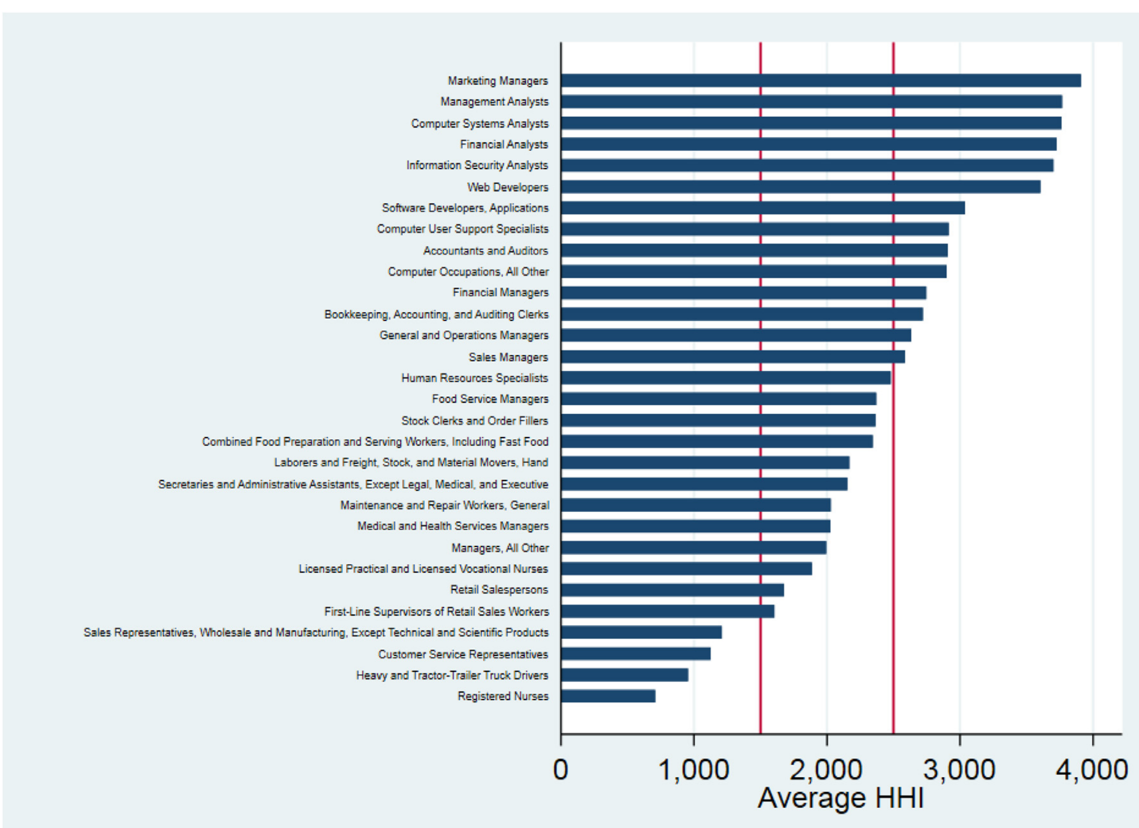


Fig. 4. Average HHI by occupation, based on vacancy shares, for the largest 30 occupations. This figure shows the average of the Herfindahl-Hirschman Index by 6-digit SOC occupation code for the 30 largest occupations as measured by number of vacancies over the period 2016Q1–2016Q4 in the Burning Glass Technologies dataset. Market shares are defined as the sum of vacancies posted by a given firm in a given market (6-digit SOC by commuting zone) and year-quarter divided by total vacancies posted in the website in that market and year-quarter.

der to observe a negative relationship between wages and applications within a SOC-6, it must be the case that there is significant worker sorting, with each worker type applying to some of the job titles within a SOC-6 and not others. In particular, inexperienced workers tend to apply to junior job titles, and experienced workers tend to apply to senior job titles within an SOC-6. This is the sense in which job titles may be a better definition of the labor market than SOC-6 occupations.

Next, instead of using the SOC-6 definition, we use the Burning Glass Technology (BGT) occupation. This classification is based on the SOC, but expands or consolidates SOC categories using the similarity of skills, education and knowledge requirements. This classification gives results (Table 1) that are almost identical to the baseline. We then broaden the occupational categories by using either the BGT broader occupation group or the 3-digit SOC (for the 3-digit SOC, we use top 60 occupations, representing 98% of vacancies). The BGT broader occupation group categorizes occupations based on similar work functions, skills, and profiles of education and training. When using either the BGT broader occupation group or the 3-digit SOC, HHI levels are very similar: the average market is a few hundred points above the 2500 threshold for high concentration, and 40% of markets are highly concentrated.

We now examine the impact of alternative geographical market definitions. As would be expected, county-level HHIs are higher than CZ-level HHIs, and state-level HHIs are lower than CZ-level HHIs (Table 1). State-level HHIs are very low and only 7% of markets are highly concentrated according to this definition. However, a state is very likely too broad a market. By contrast, a county is smaller than a commuting zone, yet it is sometimes used to define a geographic market, e.g. by the Federal Reserve to calculate banking concentration (FRB, 2014). If we adopt the county as a definition of the geography for a labor market, 78% of labor markets are highly concentrated.

Finally, we examine time aggregations other than the quarter. Table 1 shows that the average HHI calculated using monthly data is higher than the baseline, and the HHI using semesters is lower but still highly concentrated.

In summary, we find that reasonably-defined local labor markets are highly concentrated on average. In our preferred definition of the labor market, the majority of US labor markets are highly concentrated (above 2500 HHI).

4.1. Correlations between labor market concentration and wages

Measured concentration in any market is an economic outcome, codetermined with other market characteristics, such as the distribution of wages. That naturally raises questions about what concentration actually tells us about how that market operates. Fully answering that question, either empirically or theoretically, is outside the scope of this paper. But we do show some descriptive evidence that employer concentration in a labor market is associated with lower wages, which suggests that employers exercise wage-setting power in that market.

We stress that these exercises document an association, not a causal relationship, between concentration and earnings or wages at the labor market level. In particular, employers that are more productive may both pay higher wages and employ a larger share of workers (so the markets they operate in might be more concentrated). Other threats to identification may operate at the market rather than the firm level: if business cycle variation in output demand drives vacancy-posting and hiring, fewer firms may be hiring during a local recession, and those few that do may be paying lower wages conditional on the job or occupation.

The purpose of reporting these associations is to validate that the concentration estimates in Section 4 tell us something about employer power, in line with the simple oligopsony model of Boal and Ransom (1997).

Specifically, in Table 2 we report a robust negative relationship between measured concentration, as reported in the previous section, and both the posted vacancy-level salary in the BGT data and the annual earnings and average hourly wage constructed from Occupational Em-

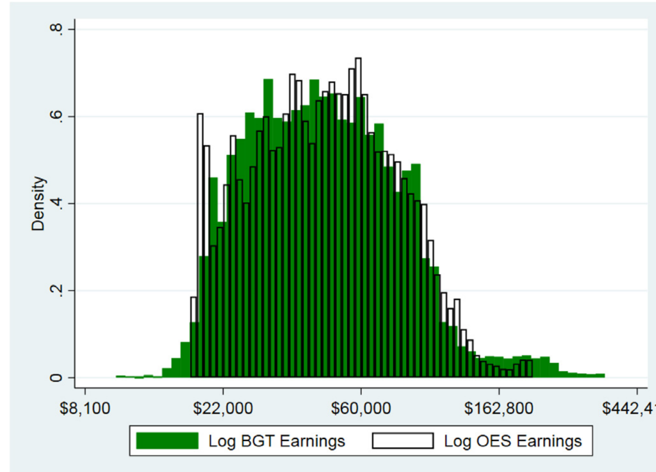


Fig. 5. Overlying histograms of the log of average annual earnings in the BGT and OES data. The plot is in log scale, but the horizontal axis labels report corresponding annual salary levels.

ployment Statistics Data. (The two data sources for annual earnings are compared in Fig. 5.) The negative relationship showed in column 1 across both occupations and geography holds whether the variation in concentration is only across occupations (column 2 with commuting zone fixed effects) or only across geography (column 3 with occupation fixed effects), and controlling for OES-measured employment in the market.

Geographic labor markets with higher population tend to exhibit both lower concentration (see Fig. 3) and higher wages. In order to filter out the omitted variable of geography or population, we can look at variation in concentration across occupations, holding the commuting zone constant (columns 2 and 5 of Table 2). As for occupational characteristics, we could think that occupations with lower pay employ more workers, whether or not those occupations are less concentrated. We control for market-level employment and find that indeed higher employment in an occupation within a commuting zone is associated with lower wages (column 5). Once we control for market-level employment separately, the correlation between concentration and earnings becomes larger (more negative) in columns 4 and 5. That suggests that occupations accounting for a larger share of employment tend to post lower wages.

The results are quite similar whether the outcome of interest is taken from the BGT posted salary or the OES market earnings or hourly wage (or quasi-market wage, since those are reported at the occupational and MSA level). The similarity of findings for these different measures of wages is noteworthy in itself, since the data sources are so different, and it suggests that the posted wages for job ads are, in fact, good signals about wages in the labor market for which the job is being posted.

It's possible that business-cycle variations in local labor demand would reduce hiring, thereby increase concentration of hiring in fewer firms, and also reduce wages. The CareerBuilder data used in Azar et al. (2020) also tracks job applications in addition to vacancies, which means it's possible to control for local labor market tightness and thereby filter out business cycle variation that affects both concentration and wages. The BGT data is more comprehensive, but at the cost of inability to control for a similar business cycle indicator. However, in Appendix E (Table E10) and Appendix F (Tables F11 and F12), we construct market-level measures of labor market tightness using other data sources: Local Area Unemployment Statistics and Quarterly Workforce Indicators, respectively. The results using tightness as a regressor confirm that the correlation between concentration and wages is not due to labor market demand fluctuations.

Appendix B (Table B6) re-runs the regressions reported here for (much broader) markets defined by 2-digit rather than 6-digit oc-

Table 2

Descriptive regressions of earnings and hourly wages on market concentration. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-6 by commuting zone by quarter level. Columns (1) and (4) allow for variation across both occupational and geographic dimensions. Columns (2) and (5) look at variation across occupations, within commuting zones. And columns (3) and (6) look at variation across commuting zones, within occupations. Columns (4)-(6) add market-level employment from OES data as a control.

Dependent Variable: Log Earnings (BGT)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0479***	-0.0428***	-0.0286***	-0.156***	-0.118***	-0.0196***
	(0.00142)	(0.00187)	(0.000815)	(0.00185)	(0.00195)	(0.00130)
Log Employment				-0.105***	-0.140***	0.00847***
				(0.00134)	(0.00154)	(0.000966)
Constant	10.62***	10.63***	10.66***	10.98***	11.28***	10.62***
	(0.00368)	(0.00460)	(0.00236)	(0.00653)	(0.00894)	(0.00428)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	207,741	207,740	207,741	193,765	193,765	193,765
R-squared	0.012	0.047	0.591	0.098	0.161	0.595
Dependent Variable: Log Earnings (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0637***	-0.0490***	-0.0316***	-0.191***	-0.143***	-0.0218***
	(0.00172)	(0.00218)	(0.000593)	(0.00199)	(0.00211)	(0.000832)
Log Employment				-0.169***	-0.208***	0.0121***
				(0.00173)	(0.00191)	(0.000842)
Constant	10.58***	10.61***	10.65***	11.34***	11.69***	10.60***
	(0.00442)	(0.00533)	(0.00157)	(0.00916)	(0.0112)	(0.00422)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	189,380	189,380	189,380	187,477	187,477	187,477
R-squared	0.022	0.044	0.914	0.189	0.255	0.916
Dependent Variable: Log Hourly Wage (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0664***	-0.0536***	-0.0312***	-0.205***	-0.158***	-0.0208***
	(0.00176)	(0.00224)	(0.000597)	(0.00203)	(0.00214)	(0.000844)
Log Employment				-0.180***	-0.219***	0.0129***
				(0.00177)	(0.00196)	(0.000853)
Constant	2.932***	2.961***	3.012***	3.725***	4.074***	2.956***
	(0.00458)	(0.00556)	(0.00160)	(0.00936)	(0.0115)	(0.00424)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	182,200	182,200	182,200	180,464	180,464	180,464
R-squared	0.024	0.045	0.917	0.206	0.271	0.918

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

cupations. It shows a similar negative relationship and similar patterns as to its magnitude in each specification as does Table 2. Appendix C (Table C7) performs the regressions for 6-digit occupations, but without fully monopsonized markets (where HHI = 10,000). Appendix D (Tables D8 and D9) does the same using unionization-related covariates, on the theory that they may mediate the effect of concentration on wages. Again, results are similar.

4.2. Occupational variation in concentration and employer market power

One question that arises for economy-wide estimates of labor market concentration is whether concentration, or employer market power, systematically varies with other labor-market-level characteristics. Specifically, do low-paid or less-educated workers suffer from a greater disadvantage in relative bargaining power due to their (presumably) greater replaceability? Or are less-educated workers better-situated vis-a-vis individual employers because they have more abundant job opportunities, either because there are more employers hiring in the occupations where they're currently employed or because, given lower levels of occupation-specific investment in skills, it's (relatively) less costly for them to transition to a different occupation?

Fully answering that question is outside the scope of this paper, but we do bring evidence to bear on the market-level covariates of labor market concentration across the economy. First, other work has found no systematic relationship between worker status in the labor market and observable indicators of employer market power. Azar et al. (2019b) estimate firm-specific supply elasticities for workers by occupation. They find median elasticities do not differ very much between low- and high-skill occupations.

Here we measure employer power using employer concentration. Figs. 6 and 7 report average market concentration (across geography) for the most-frequently-posted 30 occupations in the BGT data, ranked according to occupation average earnings and occupation average level of education required. In both cases, there's little relationship between concentration and an occupation's rank, according to either ranking.

Table 3 reports similar relationships for occupation-level correlates of concentration, but instead of the top 30 most posted occupations, the correlation table includes all the occupations in the BGT data,

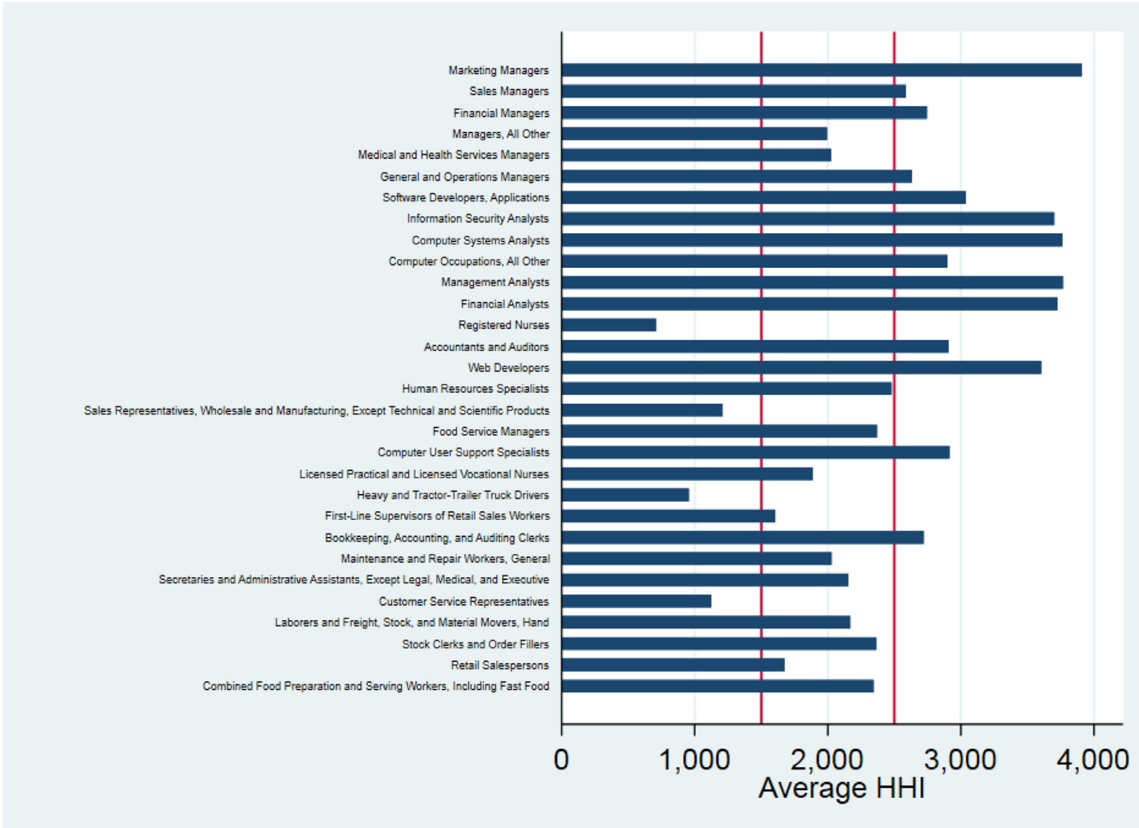


Fig. 6. Most-frequently-posted SOC-6 Occupations Ranked by Average Earnings (in BGT job postings). Concentration for a given occupation (averaged across commuting zones and quarters, in 2016) does not appear to vary systematically with an occupation's average earnings. Some occupations are systematically more concentrated than others, but such occupations appear throughout the occupation-earnings distribution.

Table 3
Correlations Between Concentration and Measures of Occupational Rank. This table reports correlations between observed average concentration, earnings, and years of required education for all 6-Digit SOC Occupations in the BGT data, averaged over commuting zones. Occupations are weighted by market-level (log) employment, so very small occupations matter little.

	Log HHI	Log OES Earnings	Education
Log HHI	1		
SE			
Log OES Earnings	-0.0658	1	
SE	0.0626		
Education	-.0432	0.7483	1
SE	0.2216	0.0000	

weighted by market-level employment. When including all the occupations, there's a slight negative correlation between occupational rank by either earnings or education, and that occupation's concentration, but the relationship is not significant so there is no robust reason to think that either higher- or lower-ranked occupations have significantly more concentrated labor markets, or (from this data) that employers wield more power over either more- or less-credentialed workers.[11]

It's worth noting that the minimum wage may play a role in this assessment of the relationship between measured employer concentration and occupational skill or rank. Empirical research documents a reallocation effect of minimum wage increases, toward larger firms in which the monopsonistic wedge between what workers are paid and their marginal product is higher (Aaronson et al. (2018) & Dustmann et al. (2020)). If that is the case, then the minimum wage may be responsible for increasing the employment share of larger firms (and thus measured concentration), and occupations where the minimum wage binds more may appear to be more concentrated than they would in the absence of minimum wage increases. The minimum wage may also bear on the interpretation of concentration-earnings regressions as in Section 4.1: increases in the minimum wage would both raise wages in the occupations they affect and increase concentration, making the estimated negative coefficient on concentration closer to zero.

5. Discussion

One potential explanation of the firm-specific earnings premia reported in Card et al. (2018) and Song et al. (2019) is a lack of competition among employers: if job offers are not frequent enough to equilibrate earnings of similar workers across firms, then firms likely have market power in wage-setting. The increase in the degree of inter-firm earnings inequality for similar workers in similar industries is an indication that firm-level wage-setting power has become relatively more important as job offers become less frequent. Empirical studies of the declining frequency of incoming job offers for employed workers (Hyatt and Spletzer, 2016) and (Molloy et al., 2016))

[11] Ranking occupations in this way may be misleading if job-filling rates, conditional on posting a vacancy, are systematically different for larger versus smaller employers within an occupation. For example, if larger employers feature higher turnover of employment, they might therefore be recruiting more frequently for a given job. In that case, a measure of effective concentration, taking into account high-frequency turnover happening at larger firms, would show higher concentration at lower-wage jobs than does our raw measure of concentration based on vacancy data. The opposite would be the case if smaller employers turn over jobs more frequently, within an occupation.

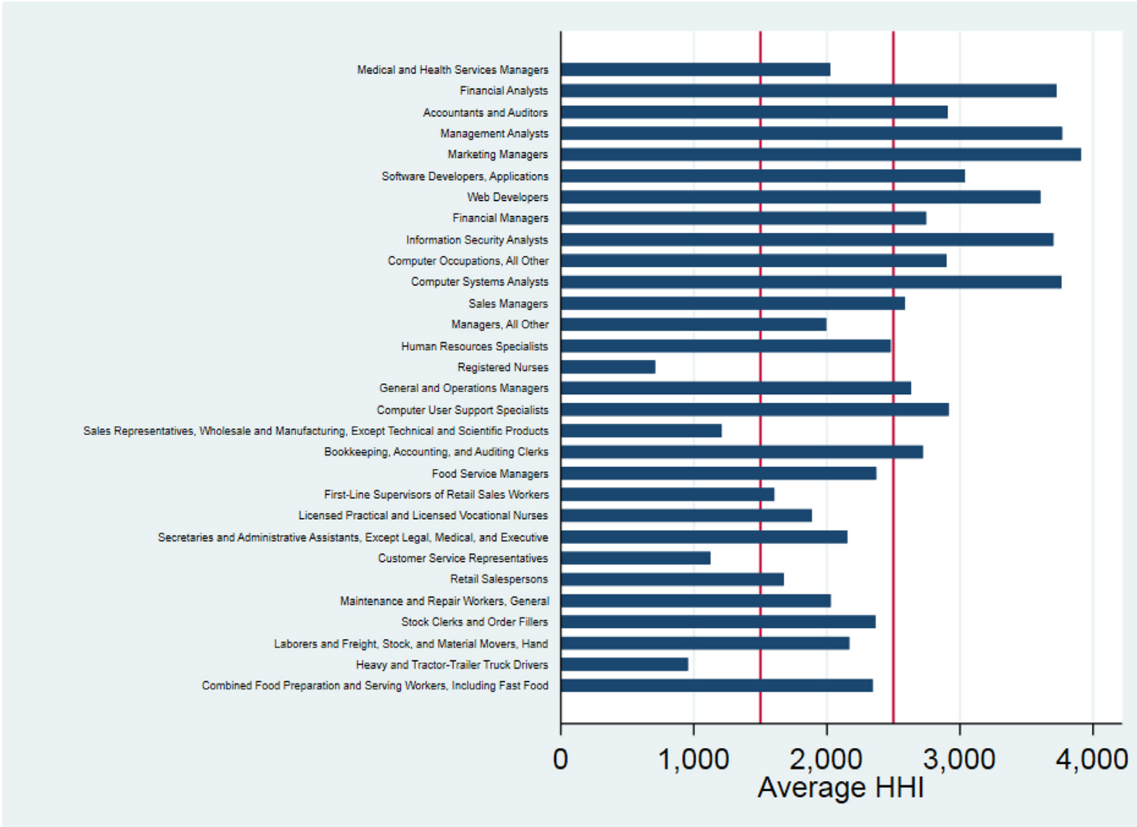


Fig. 7. Most-frequently-posted SOC-6 Occupations Ranked by Average Years of Education Required (in BGT job postings). As with occupational average earnings, concentration does not appear to vary systematically with an occupation's required years of education.

are thus consistent with a decrease in labor market competition among employers.[12]

The literature exploring the degree of market power in the labor market has generally focused on estimating elasticities of labor supply to the individual firm, as opposed to market concentration Webber, 2015). This "New Monopsony" literature takes as its starting point that monopsony power can occur in a frictional labor market even if observed labor market concentration is low, because workers are more tied to particular employers and cannot easily find another job. Monopsony can explain a number of observed labor market phenomena, including a minimal disemployment effect from increases in the minimum wage Manning (2011).

In models with monopsony power and frictional labor markets, employers trade off wages with their employees' quit rates. If workers have a high elasticity of labor supply, then firms pay them more to get them to stay. The literature generally finds low elasticities of labor supply and interprets this as evidence for firm-level monopsony power to reduce wages below the marginal product of labor.[13]

Our approach is complementary with this literature, but with a different mechanism at play. We measure market-level concentration in local and occupational labor markets for the entire US labor market at a point in time, using vacancy data rather than employment. Buyer-side market power stemming from labor market concentration is another plausible alternative mechanism for empirical findings from the New Monopsony literature. In the New Monopsony literature, job differentiation is a classic way to generate a low firm-level labor supply elasticity even when labor markets are not concentrated. In our framework, firms pay higher wages if the labor market is not concentrated and workers can expect abundant job offers. The low probability of receiving an outside job offer in concentrated labor markets leads to a low firm-level labor supply elasticity.

Thus, labor market concentration and labor market frictions may be observationally-equivalent in terms of wage effects. Azar et al. (2019b) find a strong negative relationship between firm-specific labor supply elasticity and measured concentration, and also that, according to both measures, employer market power is lower in less densely-populated labor markets (though densely-populated markets are not by any means perfectly competitive). We view the contribution of this paper as complementary with both the New and "Old" Monopsony literature, that is, it computes one measure that is a good index of employer power, while not the only source of it in practice.

6. Conclusion

Since the release of Barkai (2019), Autor et al. (2020) and De Loecker et al. (2020), and other papers documenting rising product market concentration and discussing its effect on the labor market, there has been a great deal of academic and popular interest in whether

[12] Another indicator of employer monopsony power may be the use of domestic outsourcing, such as documented in Weil (2014) and Dube and Kaplan (2010). Handwerker and Spletzer (2015) shows that occupational concentration has been rising within establishments, consistent with the notion that occupations are outsourcing jobs that were once done by employed workers. Consistent with the idea that such outsourcing is one mechanism for the exercise of monopsony power (see Weil, 2018), that paper finds that establishments whose workers are more occupationally-concentrated pay, on average, lower wages.

[13] Webber (2015); Dube and Kaplan (2010). Naidu et al. (2018) conduct simulations showing the substantial welfare losses due to monopsony based on the empirical estimates of firm-specific labor supply elasticity taken from the New Monopsony literature.

Table A4

Summary statistics for baselin labor market concentration in 2012 and 2016. This table shows summary statistics for labor market Herfindahl-Hirschman Index (HHI) under the baseline market definition, for the years 2012 and 2016 using data from Burning Glass Technologies (BGT). The baseline is calculated using commuting zones for the geographic market definition, 6-digit SOC codes for the occupational market definition, aggregating the data at the quarterly level (and then averaging over quarters for a given CZ × SOC). Concentration is calculated over the top occupations (top 200 ranked based on the number of vacancies in the case of 6-digit SOC, representing 90% of vacancies in 2016) over each year.

	Mean	Min	Max	25th Pctile.	75th Pctile.	Fraction Moderately Concentrated	Fraction Highly Concentrated
Baseline market definition 2012:							
Number of Firms (Unweighted)	8.6	1.0	1400	1.0	5.5		
HHI (Unweighted)	4752	5	10,000	1519	7600	0.11	0.64
Baseline market definition 2016:							
Number of Firms (Unweighted)	12.6	1.0	1983.8	1.5	8.3		
HHI (Unweighted)	4378	4	10,000	1232	7279	0.11	0.60

market concentration might be the cause of monopsony power, wage stagnation, and other macro labor trends.

In this paper, we make three contributions: First, we calculate measures of market concentration in local labor markets for the near-universe of 2016 online vacancy postings constructed by Burning Glass. We have shown that concentration is high (above 2500 HHI) in 60% of US labor markets according to our baseline market definition, and in at least a third of US labor markets according to alternative labor market definitions. Employment-weighted average concentration is lower at 1361, reflecting lower concentration in more populated areas. Second, we show that higher market concentration is associated with lower wages, consistent with the notion that it captures a measure of employer market power. Third, we show that at least according to that measure, there's no significant variation in employer market power across the occupational hierarchy.

In combination with a growing body of other research, the results reported here establish that, while variable, employer power in labor markets is pervasive in the US economy. Horizontal concentration is by no means the last word about measuring employer power, but its level and its covariates are important to establish as stylized facts.

Appendix A. Labor Market Concentration and Product Market Concentration in Manufacturing

A further question that arises in studying labor market concentration is the degree to which it overlaps empirically with concentration of selling in output markets. Conceptually, the phenomena are entirely different, but it may still be the case that sellers with high market share of output markets also have high market share as employers in labor markets, and that overall concentration is positively correlated on "both sides" of the market.

To investigate this question, we examine the case of manufacturing. We choose to focus on manufacturing because, unlike labor markets, the manufacturing product market is generally national (Ashenfelter et al., 2013), for example)), or even international[14], so we expect important differences between product market and labor market concentration[15] We compare labor market concentration and product market concentration, and examine the relationship of each type of concentration with occupational wages.

Since the most recent available product market HHI for manufacturing is 2012, the analysis in this section uses 2012 data from all sources. Labor market HHIs in 2012 and 2016 are similar. Concentration in 2012 is slightly higher, with an average HHI of 4752 in 2012 vs. 4378 in 2016, and 64% of markets being highly concentrated in 2012 vs. 60% in 2016 (Table A4). The data quality in 2012 may be slightly lower than in 2016 since the ratio of the number of vacancies in our cleaned dataset (aggregated at the national level) to the number of JOLTS vacancies is 0.292 in 2012 and 0.323 in 2016; similarly, the ratio of the number of vacancies in our cleaned dataset to employment in the Occupational Employment Statistics is 0.027 in 2012 and 0.043 in 2016. Product market HHI is from the Economic Census at the national NAICS-4 level. The HHI is based on the value of shipments, in order to measure concentration in sales.

We compute labor market concentration for each industry based on the occupation with the largest national employment in each industry; call this occupation the "top occupation". By choosing the largest occupation in each industry, we are more likely to find a positive correlation between labor and product market concentration than if we were using all employment, including occupations that are not particularly specific to that industry. Using the Occupational Employment Statistics (OES), we calculate the national average hourly wage for the top occupation in each industry. Using Burning Glass Technologies data, we calculate the labor market HHI for the top occupation in each industry at the commuting zone (CZ) by quarter level. To calculate this labor market HHI, we include vacancies in that occupation that are not in that industry, so that the HHI calculated here is calculated in exactly the same way as our baseline HHI for 2016. We calculate the average national labor market HHI for the top occupation in each industry by averaging first over quarters by CZ, and then over CZ weighting by OES employment in the top occupation and NAICS-4 in each CZ. Because in Azar et al. (2020), we have shown that the relationship between wages and concentration is linear in the log-log space, we log each measure of concentration here in order to correlate it with log wages.

Overall, labor market and product market concentration are positively but not very strongly correlated (Fig. A.8). The raw correlation between log labor market HHI and log product market HHI is 0.11 across the 86 industries, and 0.33 when weighing by OES employment in the top occupation. In a weighted regression of labor market HHI on product market HHI, the coefficient is significant at the 5% level. In general, labor market HHIs are much higher than product market HHI: across industries, the average product market HHI is 411 and the average labor market HHI (weighted by local employment) is 3,955. Given that product markets are national and labor markets are local, this level comparison is not surprising.

While labor and product market HHIs are positively correlated, they are far from being perfectly aligned. For example, we can compare two large industries (by employment) with similarly low product market HHI: plastics product manufacturing and cement and concrete product manufacturing, with each industry employing about 50,000 people in its top occupation. In plastics product manufacturing, the top occupation is "Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic". Plastics product manufacturing has a product market HHI of 30 (83rd most concentrated out of 86) and a

[14] For product markets that are international, US national sales concentration overestimates overall concentration in the industry. For international product markets, we expect the correlation between product market concentration and labor market concentration to be even lower than for national markets.

[15] In general, we expect a higher correlation between product market and labor market concentration for product markets that are more local, such as the retail industry.

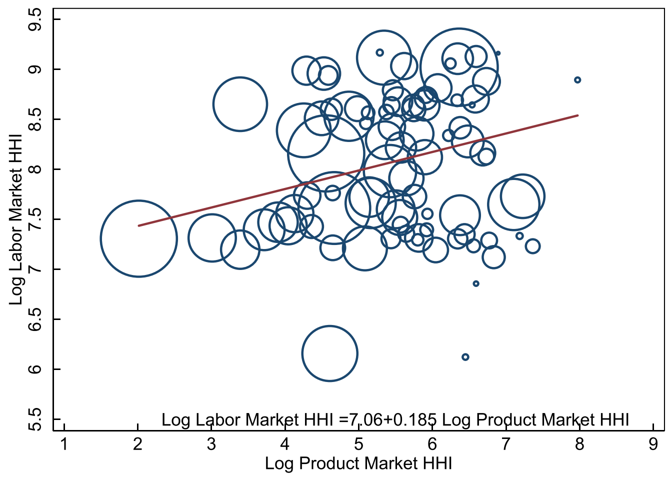


Fig. A8. Scatter of Product Market and Labor Market HHIs for Manufacturing in 2012 using top occupation. Only manufacturing industries are included; all data is for year 2012. Product market HHI is from the Economic Census at the national NAICS-4 level (based on the value of shipments). Using the Occupational Employment Statistics (OES), we determine the highest employment occupation in each industry; call this occupation the "top occupation". The size of the circles in the scatter is proportional to NAICS-4 employment in the top occupation. Using Burning Glass Technologies data, we calculate the labor market HHI for the top occupation in each industry at the commuting zone (CZ) by quarter level; to calculate HHI, we include vacancies in that occupation that are not in that industry, so that the HHI is calculated in exactly the same way as our baseline HHI for 2016. We calculate the average national labor market HHI for the top occupation in each industry by averaging first over quarters by CZ, and then over CZ weighing by OES employment in the top occupation and NAICS-4 in each CZ. The fitted line is from a regression weighing by OES national employment in the top occupation in the NAICS-4; the estimated coefficients are displayed at the bottom of the figure, and the coefficient on product market concentration is significant at the 5% level.

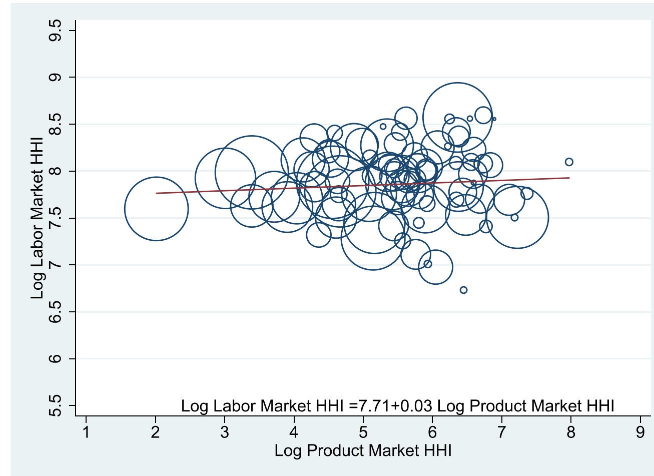


Fig. A9. Scatter of Product Market and Labor Market HHIs for Manufacturing in 2012 using all occupations. Only manufacturing industries are included; all data is for year 2012. Product market HHI is from the Economic Census at the national NAICS-4 level (based on the value of shipments). The size of the circles in the scatter is proportional to NAICS-4 employment in the industry from the Occupational Employment Statistics (OES). Using Burning Glass Technologies data, we calculate the labor market HHI for each industry at the commuting zone (CZ) by quarter level using a weighted (by employment) average of the HHI in all the occupations in the industry; to calculate HHI, we include vacancies in that occupation that are not in that industry, so that the HHI is calculated in exactly the same way as our baseline HHI for 2016. We calculate the average national labor market HHI for each industry by averaging first over quarters by CZ, and then over CZ weighing by OES employment in the NAICS-4 in each CZ. The fitted line is from a regression weighing by OES national employment in each NAICS-4; the estimated coefficients are displayed at the bottom of the figure, and the coefficient on product market concentration is not significant at the 10% level.

labor market HHI of 5726 (21st most concentrated): this industry is thus relatively unconcentrated in the product market but highly concentrated in the labor market both in relative and absolute terms (the industry that has a log HHI between 3 and 4 and is well above the fitted line in Fig. A.8). For comparison, consider cement and concrete product manufacturing, where the top occupation is "Heavy and Tractor-Trailer Truck Drivers". The cement and concrete products industry has a product market HHI of 100 (the 70th most concentrated industry) and a labor market HHI of 473 (the 85th most concentrated industry, essentially the least concentrated): the industry appears well below the fitted line in Fig. A.8, having a log product market HHI between 4 and 5 and a log labor market HHI between 6 and 6.5. In cement and concrete product manufacturing, the labor market concentration in the top occupation is low, presumably because truck drivers work in many industries besides cement and concrete products. This suggests that while plastics manufacturing firms may not have significant product market power (at least as measured by concentration), they do have significant labor market power over an occupation that is essentially specific to that industry. Whereas cement and concrete manufacturers have relatively more product market power, but less labor market power (with respect to truck drivers) than plastics manufacturers do with respect to their top occupation.

Instead of using just the top occupation for each industry, we can also use all occupations to calculate concentration. In this case, we weight HHIs by the employment in that occupation for the industry, and otherwise use the same data construction procedure as above. Labor market concentration in all occupations has no systematic relationship with industry concentration: Fig. A.9 shows that the slope is almost flat, and regression confirms that the coefficient on product market concentration is insignificant. Labor market concentration in the top occupation in each industry is thus more related to industry concentration than labor market concentration in all occupations: this is likely because non-top occupations overlap more broadly with other industries, which relaxes the relationship between industry and labor market concentration.

Labor market concentration is different from product market concentration, and occupational wages are lower when labor market concentration is higher, not when product market concentration is higher. Using the OES, we calculate the national average hourly wage by industry for the top occupation in each industry. Across industries, labor market concentration in the top occupation has a negative and statistically significant effect on wages (Fig. A.10), and the elasticity of the wage with respect to labor market concentration is about -0.1, whether weighting by employment or not (Table A5, col. 1 and 2). So, across industries, a 10% increase in labor market concentration is associated with a 1% lower wage in the top occupation. This magnitude is of the same order of magnitude as the one obtained in our previous work with CareerBuilder.com data on labor market concentration and posted wages (Azar et al., 2020)). What about product market concentration? The impact of product market HHI on wages is positive and marginally significant in unweighted regressions, but smaller and insignificant in weighted regressions (Table A5, col. 3 and 4). Including both labor market and product market HHIs in the same regression does not alter the conclusions (Table A5, col. 5 and 6): labor market concentration is negatively associated with wages while product market concentration has a much smaller positive and not always significant association with wages.

In a nutshell, we have shown that labor market concentration in manufacturing is higher than product market concentration and not per-

Table A5

Labor market concentration, product market concentration, & occupational wages in manufacturing. Only manufacturing industries are included; all data is for year 2012. Product market HHI is from the Economic Census at the national NAICS-4 level (based on the value of shipments). Using the Occupational Employment Statistics (OES), we calculate the national average hourly wage for the highest employment occupation in each industry; call this occupation the "top occupation". Using Burning Glass Technologies data, we calculate the labor market HHI for the top occupation in each industry at the commuting zone (CZ) by quarter level; to calculate HHI, we include vacancies in that occupation that are not in that industry, so that the HHI calculated here is calculated in exactly the same way as our baseline HHI for 2016. We calculate the average national labor market HHI for the top occupation in each industry by averaging first over quarters by CZ, and then over CZ weighing by OES employment in the top occupation and NAICS-4 in each CZ..

	Dependent Variable: Log Hourly Wage (OES)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Labor Market HHI	-0.0920**	-0.105**			-0.101**	-0.125***
	(0.0402)	(0.0432)			(0.0396)	(0.0469)
Log Product Market HHI			0.0481*	0.0104	0.0554**	0.0335
			(0.0253)	(0.0378)	(0.0234)	(0.0323)
Constant	3.505***	3.588***	2.497***	2.699***	3.267***	3.581***
	(0.327)	(0.337)	(0.132)	(0.186)	(0.325)	(0.378)
Weighted by national industry employment in top occupation.		✓		✓		✓
Observations	86	86	86	86	86	86
R-squared	0.064	0.097	0.037	0.003	0.113	0.126

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

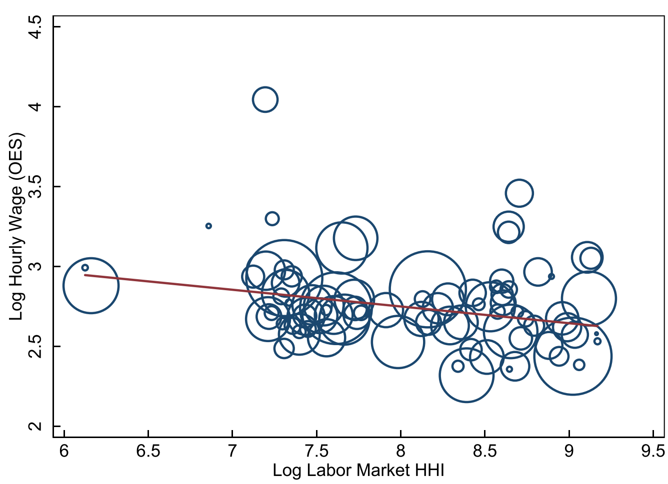


Fig. A10. Scatter of Log Wages and Labor Market HHIs for Manufacturing in 2012. Only manufacturing industries are included; all data is for year 2012. Product market HHI is from the Economic Census at the national NAICS-4 level (based on the value of shipments). Using the Occupational Employment Statistics (OES), we calculate the national average hourly wage for the highest employment occupation in each industry; call this occupation the "top occupation". The size of the circles in the scatter is proportional to NAICS-4 employment in the top occupation. Using Burning Glass Technologies data, we calculate the labor market HHI for the top occupation in each industry at the commuting zone (CZ) by quarter level; to calculate HHI, we include vacancies in that occupation that are not in that industry, so that the HHI calculated here is calculated in exactly the same way as our baseline HHI for 2016. We calculate the average national labor market HHI for the top occupation in each industry by averaging first over quarters by CZ, and then over CZ weighing by OES employment in the top occupation and NAICS-4 in each CZ. The fitted line is from a regression weighing by OES national employment in the top occupation in the NAICS-4.

fectly predicted by product market concentration. Occupational wages are negatively associated with labor market concentration, but not product market concentration. These results suggest that looking at product market concentration and product market power is not sufficient to understand competition in labor markets.

Appendix B. Concentration in 2-Digit SOC Markets

In order to ensure that our findings about employer concentration and its relationship to employer market power are robust to alternative market definitions, we conduct the regressions reported in Table 2 for markets defined by commuting zone and 2-digit, rather than 6-digit, SOC occupations.

Fig. B.11 shows the overlying histograms of BGT and OES earnings for 2-digit occupations, equivalent to Fig. 5. Fig. B.12 lists the 20 largest 2-digit occupations (according to the number of vacancies posted), ranked in order of their average concentration. Given the larger market definition, 2-digit occupations have a lower average concentration than 6-digit occupations.

Finally, Table B6 repeats the exercise from Section 4.1, but this time with the 2-digit SOC defined markets. The results are not very different from Table 2, albeit with fewer observations.

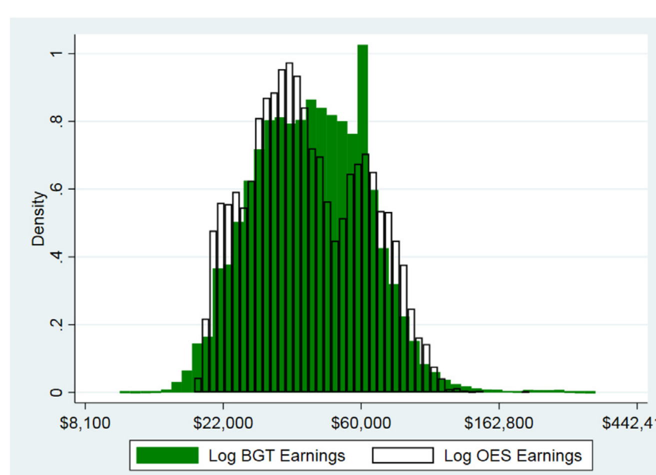


Fig. B11. Overlying histograms of the log of average annual earnings in the BGT and OES data. The plot is in log scale, but the horizontal axis labels report corresponding annual salary levels.

Table B6

Descriptive regressions of earnings and hourly wages on market concentration, for 2-digit SOC Occupations. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-2 by commuting zone by quarter level. Columns (1) and (4) allow for variation across both occupational and geographic dimensions. Columns (2) and (5) look at variation across occupations, within commuting zones. And columns (3) and (6) look at variation across commuting zones, within occupations. Columns (4)-(6) add market-level employment from OES data.

Dependent Variable: Log Earnings (BGT)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0312***	-0.0441***	-0.0224***	-0.0965***	-0.116***	-0.000954
	(0.00224)	(0.00308)	(0.00173)	(0.00329)	(0.00341)	(0.00259)
Log Employment				-0.0450***	-0.0550***	0.0198***
				(0.00248)	(0.00331)	(0.00190)
Constant	10.54***	10.51***	10.57***	10.69***	10.71***	10.47***
	(0.00725)	(0.00940)	(0.00590)	(0.0144)	(0.0231)	(0.0110)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	50,092	50,092	50,092	48,522	48,522	48,522
R-squared	0.012	0.077	0.467	0.042	0.116	0.461
Dependent Variable: Log Earnings (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0729***	-0.0867***	-0.0324***	-0.171***	-0.170***	-0.00476**
	(0.00434)	(0.00530)	(0.00188)	(0.00529)	(0.00550)	(0.00231)
Log Employment				-0.116***	-0.166***	0.0319***
				(0.00424)	(0.00559)	(0.00212)
Constant	10.37***	10.32***	10.50***	11.05***	11.48***	10.32***
	(0.0157)	(0.0189)	(0.00687)	(0.0303)	(0.0462)	(0.0152)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	26,122	26,122	26,122	26,118	26,118	26,118
R-squared	0.039	0.076	0.865	0.128	0.197	0.868
Dependent Variable: Log Hourly Wage (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0811***	-0.101***	-0.0319***	-0.186***	-0.188***	-0.00472**
	(0.00438)	(0.00530)	(0.00193)	(0.00519)	(0.00536)	(0.00234)
Log Employment				-0.124***	-0.173***	0.0312***
				(0.00406)	(0.00542)	(0.00213)
Constant	2.680***	2.609***	2.854***	3.391***	3.813***	2.678***
	(0.0164)	(0.0195)	(0.00729)	(0.0294)	(0.0456)	(0.0154)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	26,227	26,227	26,227	26,223	26,223	26,223
R-squared	0.047	0.085	0.866	0.151	0.221	0.870

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

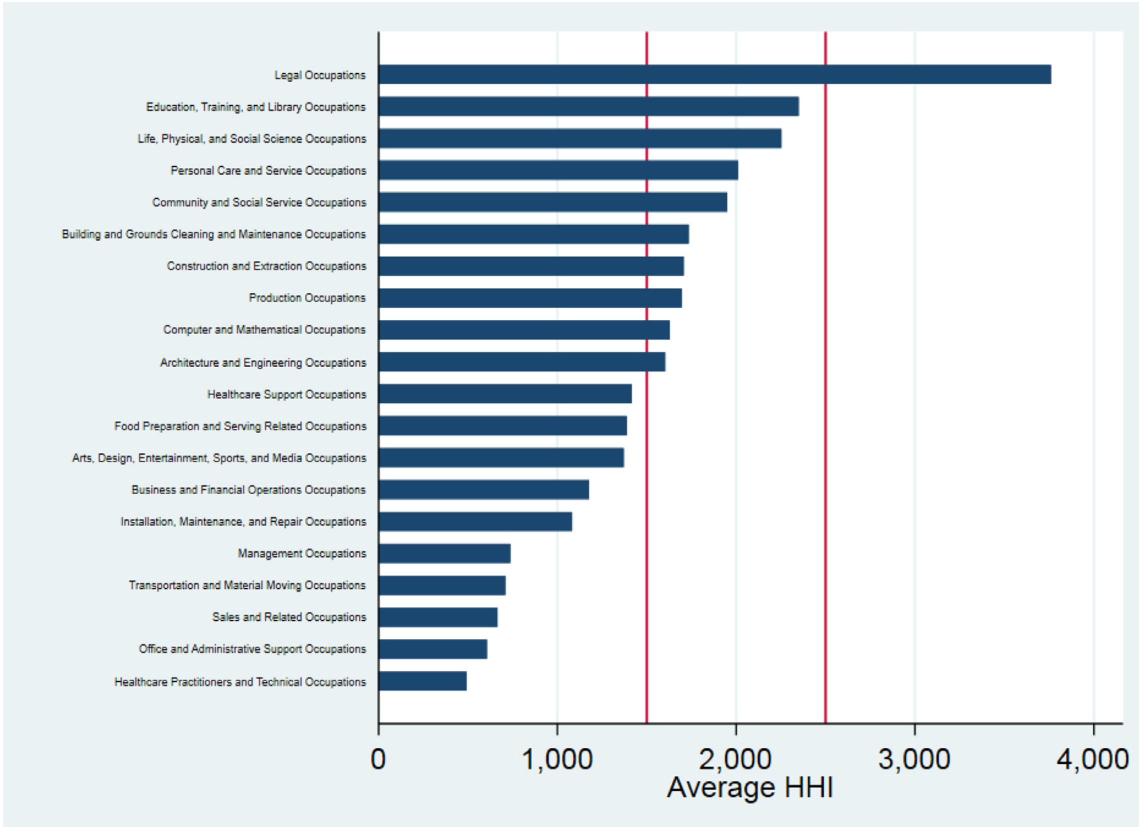


Fig. B12. Average HHI by occupation, based on vacancy shares, for the largest 20 2-digit occupations. This figure shows the average of the Herfindahl-Hirschman Index by 2-digit SOC occupation code for the 20 largest occupations as measured by number of vacancies over the period 2016Q1–2016Q4 in the Burning Glass Technologies dataset.

Appendix C. Results Without Monopsonized Markets

In this section, we report on the regressions results as in Table 2, excluding fully concentrated markets where HHI = 10,000 (Table C7). In general, the findings are quite similar to those regressions that include monopsonized markets.

Appendix D. Results With Unionization Covariates

In this section, we report on the regressions results as in Table 2, including unionization-related covariates (Tables D8 and D9). In particular, we use occupation-level union membership and union coverage rates from the Current Population Survey for 2016.[16] Because the unionization-related variables are only available at the occupation level, the specifications that employ occupation-based fixed effects are collinear and therefore not included here.

These results are not very different from Table 2. They indicate that the relationship between concentration and earnings is not mediated by unionization-related characteristics of a labor market.

Appendix E. Results With Estimates of Labor Market Tightness by Geography

In this section, we report on the regressions results as in Table 2, including commuting-zone-level estimates of labor market tightness derived from Local Area Unemployment Statistics estimates of unemployment rates at the county level (Table E10). We count the number of vacancies reported in the Burning Glass Data and compute the ratio of that count to the number of unemployed individuals reported in the LAUS data for 2016.

The aim of this approach is to control for labor market-level business cycle effects. Negative shocks to labor demand would reduce both wages and hiring, and through the latter channel, increase concentration, confounding the estimated concentration-earnings relationship. By controlling for tightness, we seek to filter out these potential business cycle effects.

Appendix F. Results With Estimates of Labor Market Tightness Computed from Hiring Rates

In this section, we report on the regressions results as in Table 2, including estimates of labor market tightness at the occupation-commuting zone level derived using the machinery of search-and-matching models of the labor market (Tables F11 and F12).

Specifically, we compute the ratio of total hires to total vacancies at the county-4-digit NAICS industry level and the Metropolitan Statistical Area-4-digit NAICS industry level. Data on hires comes from the Quarterly Workforce Indicators, a public-use version of the Longitudinal Employer-Household Dynamics matched employer-employee database assembled by the US Census from state unemployment insurance records. Data on vacancies is computed directly from the BGT dataset of job ads. The ratio of hires to vacancies is the job-filling or vacancy-filling rate in search-and-matching labor market models, and that rate is a function of market-level labor market tightness.

[16] Union membership refers to the share of workers (in a given occupation) who are union members. Union coverage means the share of workers subject to a collectively-bargained contract governing their pay and other conditions of work, whether or not they themselves are members of the union that represents them in negotiations.

Table C7

Descriptive regressions of earnings and hourly wages on market concentration for 6-digit SOC occupations, excluding monopsonized markets. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-6 by commuting zone by quarter level. Columns (1) and (4) allow for variation across both occupational and geographic dimensions. Columns (2) and (5) look at variation across occupations, within commuting zones. And columns (3) and (6) look at variation across commuting zones, within occupations. Columns (4)-(6) add market-level employment from OES data.

Dependent Variable: Log Earnings (BGT)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0559***	-0.0509***	-0.0315***	-0.164***	-0.126***	-0.0219***
	(0.00159)	(0.00203)	(0.000866)	(0.00197)	(0.00208)	(0.00135)
Log Employment				-0.107***	-0.142***	0.00879***
				(0.00137)	(0.00157)	(0.000979)
Constant	10.59***	10.61***	10.65***	10.96***	11.27***	10.61***
	(0.00423)	(0.00521)	(0.00258)	(0.00692)	(0.00945)	(0.00440)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	196,883	196,882	196,883	185,089	185,088	185,089
R-squared	0.014	0.048	0.604	0.102	0.165	0.605
Dependent Variable: Log Earnings (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0740***	-0.0607***	-0.0344***	-0.209***	-0.159***	-0.0241***
	(0.00189)	(0.00237)	(0.000641)	(0.00215)	(0.00227)	(0.000892)
Log Employment				-0.173***	-0.212***	0.0121***
				(0.00175)	(0.00193)	(0.000853)
Constant	10.55***	10.58***	10.65***	11.31***	11.68***	10.59***
	(0.00498)	(0.00601)	(0.00173)	(0.00937)	(0.0116)	(0.00424)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Observations	179,933	179,933	179,933	178,223	178,223	178,223
R-squared	0.025	0.046	0.916	0.200	0.265	0.918
Dependent Variable: Log Hourly Wage (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0765***	-0.0652***	-0.0340***	-0.223***	-0.174***	-0.0231***
	(0.00193)	(0.00243)	(0.000644)	(0.00219)	(0.00229)	(0.000902)
Log Employment				-0.183***	-0.221***	0.0127***
				(0.00179)	(0.00198)	(0.000863)
Constant	2.902***	2.929***	3.004***	3.694***	4.052***	2.950***
	(0.00513)	(0.00624)	(0.00176)	(0.00955)	(0.0118)	(0.00426)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	173,423	173,423	173,423	171,874	171,874	171,874
R-squared	0.027	0.047	0.919	0.216	0.280	0.920

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Specifically, hires are the output of the matching function that takes vacancies and unemployment as inputs. If the matching function is Constant Returns to Scale, then (dividing by vacancies) the output, the vacancy-filling rate, is a function of the input vacancies-to-unemployment ratio, or tightness. We invert the matching function in order to obtain tightness from the hires-to-vacancies ratio.

Diamond and Şahin (2016) estimate a matching function of the form

$$m = Ax^{-\alpha}$$

where x is tightness, m is the hires-to-vacancy or job-filling rate, A is the match efficiency, and α is the elasticity of matches to the tightness ratio. They estimate the following parameters:

	A	α
CPS	5.16	0.31
JOLTS	3.14	0.2

where CPS and JOLTS refer to the datasets each set of estimates is based on.

We use these two parameterizations of the matching function to compute the tightness corresponding to the hires-to-vacancies ratio at the geography-industry-quarter level.[17] We attribute those tightness estimates to individual job vacancies in the BGT data, matching on county or MSA, NAICS-4 Industry, and quarter. We then aggregate from that vacancy level to the commuting zone-SOC-quarter markets level and re-run the regressions as in Table 2 including each tightness estimate. The results from those regressions are reported in Tables F11 and F12.

Similar to the results in Appendix E, the relationship between concentration and wages doesn't change materially when log tightness is an additional regressor, which is reassuring that our baseline results in Table 2 are not driven by confounding variation in local labor demand affecting both wages and concentration.

Additionally, the coefficient estimates for tightness are positive and significant in almost all specifications, as would be predicted by any search-and-matching model of the relationship between tightness and wage-setting. The are nearer zero and insignificant in the occupation fixed effects specifications, which suggests that there's a good deal of level variation in tightness (or in the job-filling rate) by occupation.

[17] We winsorize these estimates below the 1st and above the 99th percentiles.

Table D8

Descriptive regressions of earnings and hourly wages on market concentration for 6-digit SOC occupations, using union membership as a covariate. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-6 by commuting zone by quarter level, as well as union membership rate at the occupation level. Columns (1) and (3) allow for variation across both occupational and geographic dimensions. Columns (2) and (4) look at variation across occupations, within commuting zones. Columns (3)-(4) add market-level employment from OES data. An occupation fixed-effects specification is not feasible here, since the unionization data is occupational, at the annual level.

Dependent Variable: Log Earnings (BGT)				
	(1)	(2)	(3)	(4)
Log HHI	-0.0491***	-0.0444***	-0.157***	-0.121***
	(0.00145)	(0.00190)	(0.00189)	(0.00199)
Log Employment			-0.105***	-0.140***
			(0.00137)	(0.00157)
Union Membership Rate	-0.174***	-0.186***	0.0337	0.0466**
	(0.0191)	(0.0187)	(0.0207)	(0.0206)
Constant	10.63***	10.64***	10.97***	11.27***
	(0.00434)	(0.00525)	(0.00689)	(0.00919)
Year-Quarter FE	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	YES
Occupation FE	NO	NO	NO	NO
Observations	200,796	200,795	188,208	188,208
R-squared	0.014	0.049	0.098	0.160
Dependent Variable: Log Earnings (OES)				
	(1)	(2)	(3)	(4)
Log HHI	-0.0658***	-0.0519***	-0.199***	-0.151***
	(0.00175)	(0.00222)	(0.00202)	(0.00212)
Log Employment			-0.175***	-0.215***
			(0.00175)	(0.00194)
Union Membership Rate	0.120***	0.104***	0.457***	0.452***
	(0.0197)	(0.0195)	(0.0211)	(0.0212)
Constant	10.57***	10.60***	11.32***	11.68***
	(0.00520)	(0.00610)	(0.00943)	(0.0115)
Year-Quarter FE	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	YES
Occupation FE	NO	NO	NO	NO
Observations	184,450	184,450	182,601	182,601
R-squared	0.023	0.045	0.198	0.264
Dependent Variable: Log Hourly Wage (OES)				
	(1)	(2)	(3)	(4)
Log HHI	-0.0681***	-0.0561***	-0.209***	-0.162***
	(0.00178)	(0.00227)	(0.00207)	(0.00217)
Log Employment			-0.183***	-0.222***
			(0.00180)	(0.00199)
Union Membership Rate	-0.199***	-0.184***	-0.0447	0.0345
	(0.0348)	(0.0346)	(0.0310)	(0.0302)
Constant	2.943***	2.969***	3.740***	4.085***
	(0.00565)	(0.00646)	(0.00985)	(0.0120)
Year-Quarter FE	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	YES
Occupation FE	NO	NO	NO	NO
Observations	177,270	177,270	175,588	175,588
R-squared	0.025	0.046	0.210	0.276

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D9

Descriptive regressions of earnings and hourly wages on market concentration for 6-digit SOC occupations, using union coverage as a covariate. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-6 by commuting zone by quarter level, as well as union coverage rate at the occupation level. Columns (1) and (3) allow for variation across both occupational and geographic dimensions. Columns (2) and (4) look at variation across occupations, within commuting zones. Columns (3)-(4) add market-level employment from OES data. An occupation fixed-effects specification is not feasible here, since the unionization data is occupational, at the annual level.

Dependent Variable: Log Earnings (BGT)				
	(1)	(2)	(3)	(4)
Log HHI	-0.0498***	-0.0454***	-0.158***	-0.122***
	(0.00145)	(0.00190)	(0.00189)	(0.00199)
Log Employment			-0.105***	-0.140***
			(0.00136)	(0.00157)
Union Coverage Rate	-0.0403**	-0.0535***	0.106***	0.102***
	(0.0176)	(0.0173)	(0.0190)	(0.0191)
Constant	10.62***	10.63***	10.96***	11.26***
	(0.00439)	(0.00530)	(0.00694)	(0.00925)
Year-Quarter FE	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	YES
Occupation FE	NO	NO	NO	NO
Observations	200,796	200,795	188,208	188,208
R-squared	0.013	0.048	0.098	0.161
Dependent Variable: Log Earnings (OES)				
	(1)	(2)	(3)	(4)
Log HHI	-0.0662***	-0.0526***	-0.199***	-0.151***
	(0.00175)	(0.00221)	(0.00201)	(0.00212)
Log Employment			-0.175***	-0.214***
			(0.00174)	(0.00193)
Union Coverage Rate	0.190***	0.175***	0.454***	0.435***
	(0.0182)	(0.0180)	(0.0194)	(0.0196)
Constant	10.56***	10.59***	11.32***	11.67***
	(0.00526)	(0.00617)	(0.00949)	(0.0116)
Year-Quarter FE	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	YES
Occupation FE	NO	NO	NO	NO
Observations	184,450	184,450	182,601	182,601
R-squared	0.024	0.045	0.199	0.264
Dependent Variable: Log Hourly Wage (OES)				
	(1)	(2)	(3)	(4)
Log HHI	-0.0681***	-0.0559***	-0.209***	-0.162***
	(0.00179)	(0.00227)	(0.00206)	(0.00217)
Log Employment			-0.183***	-0.222***
			(0.00180)	(0.00199)
Union Coverage Rate	0.00507	0.0165	0.0449	0.0893***
	(0.0323)	(0.0321)	(0.0287)	(0.0280)
Constant	2.928***	2.955***	3.733***	4.080***
	(0.00579)	(0.00657)	(0.01000)	(0.0121)
Year-Quarter FE	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	YES
Occupation FE	NO	NO	NO	NO
Observations	177,270	177,270	175,588	175,588
R-squared	0.025	0.046	0.210	0.276

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E10

Descriptive regressions of earnings and hourly wages on market concentration for 6-digit SOC occupations, including an estimate of labor market tightness as a covariate. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-6 by commuting zone by quarter level. The labor market tightness estimate (vacancy-to-unemployment ratio) is drawn from the BLS Local Area Unemployment Statistics data, combined with estimates of vacancies at the local level from BGT data. Columns (1) and (4) allow for variation across both occupational and geographic dimensions. Columns (2) and (5) look at variation across occupations, within commuting zones. And columns (3) and (6) look at variation across commuting zones, within occupations. Columns (4)-(6) add market-level employment from OES data.

Dependent Variable: Log Earnings (BGT)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0488***	-0.0419***	-0.0292***	-0.157***	-0.117***	-0.0199***
	(0.00146)	(0.00187)	(0.000848)	(0.00188)	(0.00196)	(0.00134)
Log Employment				-0.105***	-0.140***	0.00854***
				(0.00134)	(0.00154)	(0.000969)
Log Tightness (LAUS)	-0.00842**	0.175***	-0.00354*	-0.0121***	0.122***	-0.00208
	(0.00368)	(0.00982)	(0.00201)	(0.00364)	(0.00972)	(0.00206)
Constant	10.62***	10.44***	10.66***	10.99***	11.14***	10.62***
	(0.00496)	(0.0115)	(0.00287)	(0.00736)	(0.0142)	(0.00467)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	207,656	207,655	207,656	193,708	193,708	193,708
R-squared	0.012	0.050	0.591	0.098	0.162	0.595
Dependent Variable: Log Earnings (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0599***	-0.0488***	-0.0305***	-0.187***	-0.142***	-0.0209***
	(0.00177)	(0.00216)	(0.000625)	(0.00203)	(0.00210)	(0.000847)
Log Employment				-0.169***	-0.207***	0.0120***
				(0.00173)	(0.00191)	(0.000842)
Log Tightness (LAUS)	0.0370***	0.245***	0.00765***	0.0377***	0.157***	0.00711***
	(0.00472)	(0.0110)	(0.00146)	(0.00432)	(0.00991)	(0.00145)
Constant	10.55***	10.36***	10.65***	11.31***	11.52***	10.60***
	(0.00598)	(0.0127)	(0.00192)	(0.00991)	(0.0161)	(0.00430)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	189,380	189,380	189,380	187,477	187,477	187,477
R-squared	0.023	0.049	0.914	0.190	0.257	0.916
Dependent Variable: Log Hourly Wage (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0624***	-0.0536***	-0.0299***	-0.201***	-0.158***	-0.0196***
	(0.00181)	(0.00223)	(0.000631)	(0.00207)	(0.00213)	(0.000860)
Log Employment				-0.180***	-0.217***	0.0127***
				(0.00177)	(0.00196)	(0.000853)
Log Tightness (LAUS)	0.0386***	0.274***	0.00910***	0.0373***	0.182***	0.00852***
	(0.00484)	(0.0115)	(0.00148)	(0.00438)	(0.0102)	(0.00148)
Constant	2.900***	2.671***	3.006***	3.694***	3.874***	2.950***
	(0.00615)	(0.0134)	(0.00194)	(0.0101)	(0.0166)	(0.00433)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	182,200	182,200	182,200	180,464	180,464	180,464
R-squared	0.025	0.051	0.917	0.207	0.274	0.918

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table F11

Descriptive regressions of earnings and hourly wages on market concentration for 6-digit SOC occupations, including an estimate of labor market tightness. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-6 by commuting zone by quarter level. The labor market tightness estimate is based on the hires-to-vacancies ratio. Hires are reported in Quarterly Workforce Indicators and vacancies from the BGT data. Estimated matching functions are inverted to produce tightness estimates from that ratio. Columns (1) and (4) allow for variation across both occupational and geographic dimensions. Columns (2) and (5) look at variation across occupations, within commuting zones. And columns (3) and (6) look at variation across commuting zones, within occupations. Columns (4)-(6) add market-level employment from OES data.

Dependent Variable: Log Earnings (BGT)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0401***	-0.0479***	-0.0301***	-0.147***	-0.119***	-0.0200***
	(0.00157)	(0.00195)	(0.000922)	(0.00197)	(0.00204)	(0.00139)
Log Employment				-0.109***	-0.135***	0.00994***
				(0.00139)	(0.00160)	(0.00103)
Log Tightness (CPS)	0.0157***	0.0252***	-0.000207	0.0173***	0.0199***	-0.000643**
	(0.000388)	(0.000454)	(0.000255)	(0.000383)	(0.000442)	(0.000269)
Constant	10.63***	10.61***	10.66***	11.02***	11.25***	10.61***
	(0.00421)	(0.00505)	(0.00273)	(0.00709)	(0.00960)	(0.00475)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	185,998	185,997	185,998	175,357	175,356	175,357
R-squared	0.031	0.077	0.597	0.123	0.183	0.600
Dependent Variable: Log Earnings (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0681***	-0.0594***	-0.0331***	-0.191***	-0.149***	-0.0224***
	(0.00176)	(0.00220)	(0.000622)	(0.00205)	(0.00215)	(0.000863)
Log Employment				-0.161***	-0.198***	0.0128***
				(0.00175)	(0.00193)	(0.000849)
Log Tightness (CPS)	0.0315***	0.0369***	-0.000234	0.0239***	0.0250***	-0.000314*
	(0.000520)	(0.000535)	(0.000173)	(0.000480)	(0.000486)	(0.000173)
Constant	10.53***	10.55***	10.64***	11.26***	11.59***	10.59***
	(0.00465)	(0.00558)	(0.00167)	(0.00945)	(0.0117)	(0.00426)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	175,775	175,775	175,775	174,079	174,079	174,079
R-squared	0.078	0.106	0.917	0.227	0.290	0.918
Dependent Variable: Log Hourly Wage (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0720***	-0.0678***	-0.0326***	-0.207***	-0.167***	-0.0214***
	(0.00179)	(0.00225)	(0.000627)	(0.00208)	(0.00215)	(0.000876)
Log Employment				-0.172***	-0.208***	0.0134***
				(0.00178)	(0.00197)	(0.000863)
Log Tightness (CPS)	0.0342***	0.0401***	-0.000198	0.0267***	0.0283***	-0.000288*
	(0.000535)	(0.000550)	(0.000176)	(0.000487)	(0.000491)	(0.000175)
Constant	2.876***	2.881***	3.001***	3.641***	3.957***	2.943***
	(0.00478)	(0.00577)	(0.00170)	(0.00962)	(0.0119)	(0.00430)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	169,161	169,161	169,161	167,625	167,625	167,625
R-squared	0.087	0.116	0.920	0.251	0.313	0.921

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table F12

Descriptive regressions of earnings and hourly wages on market concentration for 6-digit SOC occupations, including an estimate of labor market tightness. This table reports labor-market-level regressions of earnings and wage data on measured market concentration described in Section 4, for markets defined at the SOC-6 by commuting zone by quarter level. The labor market tightness estimate is based on the hires-to-vacancies ratio. Hires are reported in Quarterly Workforce Indicators and vacancies from the BGT data. Estimated matching functions are inverted to produce tightness estimates from that ratio. Columns (1) and (4) allow for variation across both occupational and geographic dimensions. Columns (2) and (5) look at variation across occupations, within commuting zones. And columns (3) and (6) look at variation across commuting zones, within occupations. Columns (4)-(6) add market-level employment from OES data.

Dependent Variable: Log Earnings (BGT)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0401***	-0.0479***	-0.0301***	-0.147***	-0.119***	-0.0200***
	(0.00157)	(0.00195)	(0.000922)	(0.00197)	(0.00204)	(0.00139)
Log Employment				-0.109***	-0.135***	0.00994***
				(0.00139)	(0.00160)	(0.00103)
Log Tightness (JOLTS)	0.0101***	0.0162***	-0.000133	0.0112***	0.0129***	-0.000415**
	(0.000250)	(0.000293)	(0.000165)	(0.000247)	(0.000285)	(0.000174)
Constant	10.65***	10.65***	10.65***	11.05***	11.29***	10.61***
	(0.00436)	(0.00510)	(0.00283)	(0.00719)	(0.00955)	(0.00488)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	185,998	185,997	185,998	175,357	175,356	175,357
R-squared	0.031	0.077	0.597	0.123	0.183	0.600
Dependent Variable: Log Earnings (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0681***	-0.0594***	-0.0331***	-0.191***	-0.149***	-0.0224***
	(0.00176)	(0.00220)	(0.000622)	(0.00205)	(0.00215)	(0.000863)
Log Employment				-0.161***	-0.198***	0.0128***
				(0.00175)	(0.00193)	(0.000849)
Log Tightness (JOLTS)	0.0203***	0.0238***	-0.000151	0.0154***	0.0161***	-0.000203*
	(0.000335)	(0.000345)	(0.000112)	(0.000310)	(0.000313)	(0.000111)
Constant	10.59***	10.61***	10.64***	11.30***	11.63***	10.59***
	(0.00461)	(0.00548)	(0.00167)	(0.00933)	(0.0115)	(0.00427)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	175,775	175,775	175,775	174,079	174,079	174,079
R-squared	0.078	0.106	0.917	0.227	0.290	0.918
Dependent Variable: Log Hourly Wage (OES)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log HHI	-0.0720***	-0.0678***	-0.0326***	-0.207***	-0.167***	-0.0214***
	(0.00179)	(0.00225)	(0.000627)	(0.00208)	(0.00215)	(0.000876)
Log Employment				-0.172***	-0.208***	0.0134***
				(0.00178)	(0.00197)	(0.000863)
Log Tightness (JOLTS)	0.0220***	0.0259***	-0.000128	0.0172***	0.0182***	-0.000186*
	(0.000345)	(0.000355)	(0.000113)	(0.000314)	(0.000317)	(0.000113)
Constant	2.931***	2.945***	3.000***	3.684***	4.003***	2.942***
	(0.00473)	(0.00565)	(0.00170)	(0.00949)	(0.0117)	(0.00431)
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Commuting Zone FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	NO	YES	NO	NO	YES
Observations	169,161	169,161	169,161	167,625	167,625	167,625
R-squared	0.087	0.116	0.920	0.251	0.313	0.921

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.labeco.2020.101886

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