Concentration in U.S. local labor markets: evidence from vacancy and employment data*

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February 15, 2019

Abstract

This paper characterizes the cross-sectional and time-series properties of concentration in employment, job creation, and vacancy flows across U.S. local labor markets. We proceed in three steps: first, we derive conditions for indices of labor market concentration to be appropriate proxies for monopsony power. Then, we compute Herfindahl-Hirschman Indices at the local labor market level using data on the universe of online vacancies (BGT) and the universe of employers (LBD). Finally, we document that labor market monopsony does not manifest itself only through a negative effect on the level of wages, but also through a positive effect on the demand for skills. We find that (i) in the last decade, at most 5% of new U.S. jobs are in moderately concentrated local markets; (ii) *local* labor market concentration decreased over time, dropping by at least 25% since 1976. We reconcile our findings to previous studies on increasing *national* concentration through a statistical decomposition which implies that the covariance between a local labor market's size and its concentration level decreased over time. When it comes to the effects of monopsony, we find that a 1% increase in local labor market concentration is associated with a 0.14% decrease in average hourly wages and an increase in the number of jobs requiring cognitive and social skills equal to 10-13% of the mean ("upskilling"). We conclude that our evidence is consistent with the presence of employers' market power and discuss how upskilling constitutes a policy challenge not readily addressed by increases in the minimum wage.

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1 Introduction

The extent and variation of concentration in the labor market is crucial to understand the role employers' market power potentially plays in several recent macroeconomic trends of concern, for example the decline in labor market fluidity, sluggish wage growth, and inequality increases. In addition to these macroeconomic consequences, employers' monopsony power may affect individual workers' welfare through its effects on the characteristics of jobs, notably wages and tasks. Understanding how these effects take place is fundamental to devise appropriate policy responses. In this paper, we expand the current evidence on labor market concentration in the U.S. using comprehensive sources on both labor market stocks and flows. We consider concentration in employment, job creation, and vacancy flows across U.S. local labor markets and characterize its cross-sectional and time-series properties in detail.

Before analyzing concentration in U.S. labor markets, we derive conditions for indices of concentration based on firm-level shares, such as the Herfindahl-Hirschman Index (HHI), to be appropriate proxies for monopsony power. We find that this is the case if labor supply elasticities at the firm-level are decreasing in firm size. While previous work has already suggested that employment HHIs are suitable proxies for capturing monopsony in the labor market, we provide an explicit justification for this approach through a simple theoretical framework. Consider that employment HHIs measure the presence of large employers in a local labor market based on each employer's relative size with respect to all other firms in the labor market. Therefore, the market-level employment HHI is a good proxy for monopsony if the employers' ability to compensate their workers below their marginal product ("markdown") is increasing in their size. As we develop this intuition, we find that this condition is verified whenever labor supply elasticities at the firm-level are decreasing in a firm's employment share.

We propose an empirical strategy to verify whether labor supply elasticities are decreasing in firm size. To do so, we exploit the richness of Census data and estimate markdowns directly from establishment-level information for the manufacturing sector, following closely the approach in De Loecker and Warzynski (2012). In our baseline measure for markdowns, we assume that firms take monopsony forces into account by internalizing a finitely elastic labor supply curve. In the absence of labor adjustment costs, markdowns can be calculated as the wedge between (i) the ratio of the output elasticity of labor and its revenue share, and (ii) a firm's price-cost markup. We use this insight to devise an estimation procedure that delivers firm-level markdown estimates even in the presence of labor adjustment costs.

After establishing when HHIs reflect both local labor market concentration and monopsony power, we compute HHIs at the local labor market level using data on the universe of online vacancies (BGT) and the universe of employers (LBD). Using the HHI of employment, job creation, and vacancy flows, we find little evidence of widespread or increasing concentration in the U.S. labor market. In fact, we show that (i) in the last decade, at most 5% of new U.S. jobs are in moderately concentrated local markets; (ii) local labor market concentration decreased over time, dropping by at least 25% since 1976.

We reconcile our findings on declining *local* labor market concentration to previous studies on increasing *national* concentration through a statistical decomposition in the spirit of Olley and Pakes (1996). More precisely, we show that local concentration can be decomposed into three terms: national concentration, the covariance between the size of a local market and its concentration level, and a residual that reflects the deviation of industry-level concentration from its unconditional average across local markets. We find that an increasing national trend is compatible with a decreasing trend in local concentration whenever the dispersion in industry-level concentration or the covariance between a local labor market's size and its concentration level decreased over time. When we verify empirical support for these conditions, we find that both hold in the data.

We confirm the negative correlation between local labor market concentration and average wages — first documented in Azar, Marinescu and Steinbaum (2017) and Benmelech, Bergman and Kim (2018) —, though we find a smaller elasticity of average and median wages to concentration than previous studies. In particular, we estimate that a 1% increase in local labor market concentration is associated with a 0.14% decrease in average hourly wages. This is perhaps unsurprising, as we investigate the relationship between labor market concentration and *realized* wages, while the former studies focused on *posted* wages. Both margins are relevant and we see these results as complementary: the large negative association between posted wages and concentration highlighted in Azar, Marinescu and Steinbaum (2017) underlines how the initial bargaining position of employers changes as a result of their competitive position in the local labor market. Our finding, on the other hand, suggests that employers' market power influences more the marginal than the average worker.

Finally, we document that monopsony power does not manifest itself only through a negative effect on the level of wages, but also through a positive effect on the demand for skills. Indeed, when labor is heterogeneous, monopsony potentially affects both the quantity and the quality of labor. We show that the latter effect is quantitatively important by correlating the skill content of new jobs (vacancies) to the level of local labor market concentration. Following the skill categorization process of Deming and Kahn (2018), and Hershbein and Kahn (2018), we show that the effect(s) of labor market concentration on the demand for skills is positive and particularly strong for social and cognitive skills: a 1% increase in the market-level HHI increases the number of job postings that require social (cognitive) skills by 0.117 (0.104) units. Compared to the average number of postings containing this skills, these numbers are large as they represent 10% and 13% of their respective means. This novel result holds even when we restrict ourselves to within-firm level variation. All in all, the data supports a strong association of local labor market concentration with both lower wage levels and increased demand for skills ("upskilling").

We conclude that, taken together, our evidence is consistent with the presence of employers' market power in U.S. local labor markets. However, we argue that the upskilling effects we document in this paper constitute a policy challenge that is not readily addressed by traditional instruments such as increases in the minimum wage. On the other hand, we find little evidence of increased employers market power in U.S. local labor markets since the 1970s, and conclude that the trends in local labor market concentration are unlikely to explain *per se* the pervasive decline in labor market fluidity or increase in income inequality of the last decades.

CONTRIBUTION TO THE LITERATURE. A substantial body of research has recently focused on secular trends in the U.S. economy. The topics cover a wide spectrum of outcomes from the decline in the labor share (Karabarbounis and Neiman, 2013; Elsby, Hobijn and Sahin, 2013) to the drop in aggregate dynamism and labor market fluidity (Davis and Haltiwanger, 2014; Decker, Haltiwanger, Jarmin and Miranda, 2014). A related literature has documented a contemporaneous increase in markups and industry-level concentration of sales, and suggested that the latter could be a unifying explanation behind many of the secular trends (De Loecker and Eeckhout, 2017; Autor et al., 2017 and Eggertsson, Robbins and Wold, 2018). These works interpret the rise in sales concentration as evidence of lower competition in output markets. However, this line of thought has been recently contested by Rossi-Hansberg, Sarte and Trachter (2018). The authors, in fact, document that, although national sales concentration has increased somewhat, *local* sales concentration has declined rather steadily since at least the mid-1990s.

Our paper focuses on concentration in U.S. local labor markets. As such, we complement the literature on concentration in the output market mentioned above. Specifically, we document a pronounced decreasing trend in local labor market concentration since the mid 1970s, that is akin to the result for the output markets in Rossi-Hansberg, Sarte and Trachter (2018). In addition, we explicitly investigate the interpretation of concentration as evidence of market power, and provide a testable implication for when this is the case.

We also contribute to a recently reinvigorated research agenda on labor market monopsony. Most literature refers to monopsony power as a firm's ability to compensate its workers below their marginal product (Boal and Ransom, 1997). Monopsony is a well-studied topic in labor economics: Ashenfelter, Farber and Ransom (2011) provide an excellent review of the literature. In recent years, several studies have provided empirical evidence of employer market power, though often in very specialized settings and with a limited scope. Staiger, Spetz and Phibbs (2010) use an exogenous change in wages at Veterans Affairs hospitals as a natural experiment to investigate the extent of monopsony in the nurse labor market. Matsudaira (2014) also studies the nurse labor market, using random variation induced by the passage of a state minimum nurse staffing law. Falch (2010) and Ransom and Sims (2010) focus instead on the teachers' labor market in Norway and Missouri, respectively. An exception to this very specialized approach is Webber (2015), who uses administrative data for U.S. workers and firms to estimate labor supply elasticities at the employer-level.

Our paper takes, instead, a macroeconomic approach and uses data for the universe of online vacancies and establishments in the U.S. economy. Recent works by Azar, Marinescu and Steinbaum (2017) and Azar et al. (2018) also favor an economy-wide approach, though the authors do not use administrative data on employment and job flows, nor investigate changes in skill demand associated to labor market concentration. On the other hand, the authors document a robust negative association between labor market concentration and posted wages, a fact we also find for realized wages. A recent paper by Benmelech, Bergman and Kim (2018) uses administrative data on employment, but only for the manufacturing sector, to relate this negative association to import penetration from China. In a recent paper, Rinz (2018) studies labor market concentration in all industries; using data on firm-level employment stocks, he documents a negative time trend consistent with our findings. On the other hand, as mentioned, Autor et al. (2017) find an *increasing* trend in the national concentration of employment using Census data for selected industries. This paper shows that the decline in local labor market concentration is robust across various datasets and measures, including job creation and vacancy flows. In addition, our paper complements the current literature on monopsony in another significant way: we reconcile the increasing national trend with the local decreasing one by exploiting a statistical decomposition in the spirit of Olley and Pakes (1996) and documenting a negative time trend in the covariance between a local market's size and its level of concentration.

Finally, we round up our analysis by documenting a moderate average level of labor market concentration in the cross-section, which nonetheless results in a robust association of labor market concentration with upskilling and wage compression. Our investigation of the relationship between concentration and the demand for various skills is novel to the monopsony literature and complements recent papers that investigate heterogeneity in the returns to skills (Deming, 2017; Deming and Kahn, 2018; Hershbein and Kahn, 2018).

Overview of this paper. This paper is organized as follows. In section 2, we detail our measures of labor market concentration and provide some conditions that are required for the HHI of employment to be a good proxy for monopsony power. Then, we introduce our data sources in section 3 and discuss the strengths and pitfalls of our empirical strategy. In section 4, we document concentration trends in various measures of employment, and discuss how to reconcile the diverging patterns between local and national trends. Then, we proceed with our wage compression and upskilling results. We also explore heterogeneity in these effects across occupations. Finally, section 7 takes stock of all our empirical findings and concludes.

2 Measures of labor market concentration

Our primary measure of labor market concentration is the Herfindahl-Hirschman index (HHI). The HHI is a canonical way to summarize the level of concentration in output markets and has been increasingly popular in studies of labor markets as well (see, for example, Azar, Marinescu and Steinbaum, 2017; Azar et al., 2018; Benmelech, Bergman and Kim, Benmelech, Bergman and Kim, 2018 and Rossi-Hansberg, Sarte and Trachter, 2018). The choice of the HHI as our primary measure facilitates comparison with the recent literature on labor market concentration, though it is hardly the only approach to this complex measurement problem. In this section, we discuss how different approaches relate to each other and offer a unifying view of the results provided by previous studies.

We first survey the different measures of labor market concentration used in the literature, emphasizing the diverse definitions of "markets" and the corresponding aggregate measures. Then, we provide conditions that illustrate when a popular measure of concentration, the HHI, is also a suitable measure of employer market power. We also sketch a methodology to test these conditions by estimating labor supply elasticities at the establishment level (Manning, 2003; Matsudaira, 2014; Webber, 2015).

2.1 Concentration measures

We adopt the Herfindahl-Hirschman index (HHI) as our main measure of market-level concentration and define it as:

$$\text{HHI}_{mt} = \sum_{f \in F(m)} \left(\frac{x_{ft}}{X_{F(m)t}} \right)^2 \text{ s.t. } X_{F(m)t} = \sum_{f' \in F(m)} x_{f't}$$

where m denotes a market, $F(m)$ the set of firms in market m and x is a measure of size (often employment or sales). We illustrate different empirical strategies to define m in what follows.

By construction, the HHI ranges from 0 to 1 — where a value of 1 indicates maximum concentration, i.e. the presence of only one active seller/employer in a specific market-year. The Department of Justice (DOJ) suggests that markets whose HHI is higher than 0.25 are "concentrated". We will follow this nomenclature from time to time as well. It is also useful to keep in mind that, if firm were equally-sized, the inverse of the HHI would be equal to the number of employers in a market.

As a robustness test, we also study concentration measures in which we only consider the activity of the top 4 (or 20) firms. This measure is defined as:

$$\text{CR}^{n}_{mt} = \sum_{f \in F(m;n)} \frac{x_{ft}}{X_{F(m)t}} \tag{1}$$

where $F(m;n)$ denotes the largest n firms in market m in terms of x.

When it comes to measuring *aggregate* concentration, the literature has focused on two ways of combining market-level measures. Under the first approach, HHI are constructed at the industry level (m=industry) and are then aggregated through employment or sales weights. Following Autor et al. (2017), we refer to these as measures of **national** concentration:

$$\begin{aligned} \text{NATIONAL}_t &= \sum_{j \in J} \omega_{jt} HHI_{jt} \qquad (2) \\ &= \sum_{j \in J} \omega_{jt} \left[\sum_{f \in F(j)} \left(\frac{x_{ft}}{X_{F(j)t}} \right)^2 \right] \quad \text{s.t. } X_{F(j)t} = \sum_{f' \in F(j)} x_{f't} \end{aligned}$$

where $F(j)$ denotes the set of firms in industry j. As mentioned, outcomes x_{ft} and weights ω_{jt} can be defined through either sales, employment, payroll or vacancies. Note that if outcomes are defined through, for example, sales, then weights do not have to necessarily correspond to sales. This specific measure of national concentration has been adopted by Autor, Dorn, Katz, Patterson and Van Reenen (2017) who define their HHIs through sales and employment whereas aggregation occurs through sales shares.

Autor, Dorn, Katz, Patterson and Van Reenen (2017) also provide aggregate national concentration measures based on the industry-level prominence of the top 4 (or 20) firms:

$$\mathrm{CR}_t^n = \sum_{f \in J} \omega_{jt} \sum_{f \in F(j;n)} \frac{x_{ft}}{X_{F(j)t}} \tag{3}$$

where $F(j;n)$ denotes the largest n firms in industry j in terms of sales or employment.

In contrast to the national approach, Rossi-Hansberg, Sarte and Trachter (2018)) have argued that product market competition is better captured at the local level. Therefore, product (or labor) markets are defined at through industry-*location* cells (for example, m is an industry-county pair). Denote locations by ℓ, then an aggregate measure of **local** concentration is:

$$\begin{aligned} \mathrm{LOCAL}_t &= \sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} HHI_{j\ell t} \qquad (4) \\ &= \sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} \left[\sum_{f \in F(j,\ell)} \left(\frac{x_{f\ell t}}{X_{F(j,\ell)t}} \right)^2 \right] \text{ s.t. } X_{F(j,\ell)t} = \sum_{f' \in F(j,\ell)} x_{f'\ell t} \end{aligned}$$

In a similar fashion to national concentration, outcomes and weights can be defined through a variety of variables. Rossi-Hansberg, Sarte and Trachter (2018) adopt a local concentration measure akin to (4) through sales HHI and employment weights in the NETS data. Similarly, Rinz (2018) has constructed local employment concentration measures with HHIs and weights defined through employment using Census data. In this paper, we use a variety of data sources on firm-level employment, job creation, sales, and vacancies to explore different approaches to computing aggregate labor market concentration and relate them to each other.

2.2 Monopsony and labor market concentration

The Herfindahl-Hirschman index based on employment is a natural measure of labor market concentration; however, it is not obvious that this measure also captures a labor market's degree of monopsony. Azar, Marinescu and Steinbaum (2017) argue that an advantage of this specific measure is that there are guidelines specified by the DOJ/FTC that determine what constitutes a "concentrate" market. While we recognize that these guidelines are informative, in this section we illustrate the relationship between concentration and monopsony using an approach in the spirit of De Loecker and Eeckhout (2017). Specifically, we offer some conditions under which the HHI is not only a natural measure for labor market concentration but also a suitable measure for employers' market power.

Define employers' market power at the labor market level as an employment-weighted average of individual firms' monopsony power:

$$\mathcal{M} = \sum_{i \in m} \omega_i \mu_i \tag{5}$$

where μ_i is some measure of a firm i's monopsony power and ω_i denotes its employment share in labor market m. A commonly used measure of μ_i is a firm's ability to compensate its workers below its marginal revenue product of labor. When this gap is expressed in percentage terms, it is also referred to as a firm's "markdown".

A firm's markdown is monotonically decreasing in its perceived labor supply elasticity. To see this, consider a firm's profit maximization problem:

$$\max_{N \geq 0} F(N) - w(N)N$$

Then, a firm's optimality condition can be rearranged as:

$$\begin{aligned} F'(N^*) &= \left[\frac{w'(N^*)N^*}{w(N^*)} + 1\right] w(N^*) \\ &= \left[\frac{\varepsilon_S + 1}{\varepsilon_S}\right] \cdot w(N^*) \end{aligned} \tag{6}$$

where the firm's perceived elasticity of labor supply is defined as

$$\varepsilon_S^{-1} \equiv \frac{w'(N)N}{w(N)}\Big|_{N=N^*}$$

Therefore, a firm's markdown is one-to-one with its labor supply elasticity:

$$\mu = \frac{\varepsilon_S + 1}{\varepsilon_S}$$

From the derivation above, we conclude that the HHI perfectly captures employers' market power at the labor market level whenever firms' markdowns are proportional to their size, i.e. $\mu_i \propto s_i$ implies HHI $\propto \mathcal{M}$.

Assuming that $\mu_i \propto s_i$ requires specific and stringent functional form assumptions on a firm's production technology and the preference structure of workers. Therefore, we argue that the HHI is an appropriate (though, nor perfect) proxy for employers' market power whenever a weaker condition occurs; that is, when markdowns are increasing in a firm's size (or employment share). In other words, if markdowns tend to be higher for larger firms and large firms are more common in more concentrated markets, then the HHI is a good measure of employers' labor market power. Following this reasoning, we only need to characterize conditions under which markdowns increase with a firm's employment share. Equation (6) implies that this occurs whenever a firm's perceived labor supply elasticity is decreasing in its size. We conclude that, under the assumption that firms' labor supply elasticities are decreasing in their size, the HHI of employment is a reasonable measure for employers' market power.

We test the assumption of a positive relationship between a firm's size and the labor supply elasticity it faces by exploiting the insights of Hall (1986) and De Loecker and Warzynski (2012). Specifically, we obtain markdowns at the establishment level by structurally estimating labor supply elasticities. To do so, we infer price-cost markups through the gap between a flexible input's output elasticity and its revenue share. Note that this is valid as long as there exists at least one flexible input, though we do not require that this input is labor. In fact, in the next section, we show how to use De Loecker and Warzynski (2012)'s methodology when labor adjustments are costly but at least one of the other production inputs is free from adjustment costs. We also illustrate how interpret the gap between an input's output elasticity and its revenue share in this framework.

Without loss of generality, consider the cost minimization problem of a firm in labor only:

$$\min_{N \geq 0} w(N) \cdot N + A(N) \;\text{ s.t. }\; F(N) \geq Y \tag{7}$$

where $A(N)$ denotes a firm's labor adjustment costs.[1] Denoting the associated Lagrangian multiplier by λ, a firm's optimality condition can be written as:

$$w'(N) \cdot N + A'(N) = \lambda F'(N)$$

After some manipulation, we can write the above equation as:

$$\frac{\varepsilon_S + 1}{\varepsilon_S} + \frac{A'(N)N}{A(N)} \cdot \alpha_{A(N)} \cdot \alpha_N^{-1} = \nu^{-1} \cdot \frac{F'(N)N}{F(N)} \cdot \alpha_N^{-1} \tag{8}$$

where $\alpha_{A(N)}$ and α_N denote the revenue share of labor and labor adjustment cost, respectively. Furthermore, ν is a firm's price-cost markup. Note that α_N is directly observable in most data sets, whereas markups and output elasticities can be estimated in manufacturing markets using insights from De Loecker and Warzynski (2012) and Ackerberg, Caves and Frazer (2015). If, furthermore,

[1]For simplicity, we abstract from dynamic labor adjustment costs.

we are able to infer a firm's elasticity of adjustment cost $\frac{A'(N)N}{A(N)}$ and its revenue share of labor adjustment cost $\alpha_{A(N)} = \frac{A(N)}{P \cdot Y}$, then a firm's markdown $\mu = \frac{\varepsilon_S + 1}{\varepsilon_S}$ can also be estimated, providing a direct estimate of employers' market power.[2] Markdown estimation is, therefore, an alternative methodology to measure employers' market power that complements approaches based on the HHI.

Having clarified how different measures of concentration relate to each other and which conditions ensure that concentration indices capture monopsony power, we proceed to provide estimates of labor market concentration using comprehensive data from a variety of firm-level sources: employment stock, job creation flows and total payroll from Census data, and vacancy flows from Burning Glass Technologies.

3 Data

We use two sources of data to investigate trends in sales and labor market concentration: vacancy data from Burning Glass Technologies (BGT), and job data from the Longitudinal Business Database (LBD).

3.1 BGT

The BGT data is a unique source of micro-data that contains approximately 160 million electronic job postings in the U.S. economy spanning the years 2007 and 2010–2017. These job postings were collected and assembled by Burning Glass Technologies, an employment analytics and labor market information company, that examines over 40,000 online job boards and company websites to aggregate the job postings, parse, and deduplicate them into a systematic, machine-readable form, and create labor market analytics products. With the breadth of this coverage, the resulting database purportedly captures the near-universe of jobs posted online, estimated to be near 80% of total job ads. Using BGT vacancy data allows us to compute the concentration of job openings, thus zeroing in on concentration in local labor demand and computing an index of concentration that reflects how many employers are active in the hiring process in a local market.

The BGT data has both extensive breadth and detail. Unlike sources of vacancy data that are based on a single job board such as `careerbuilder.com` or `monster.com`, BGT data span multiple

[2] For example, under quadratic adjustment costs the former elasticity is simply equal to 2, while estimates of $\alpha_{A(N)}$ can be obtained from an estimation procedure akin to Cooper, Haltiwanger and Willis (2007).

job boards and company sites. The data are also considerably richer than sources from the Bureau of Labor Statistics, such as JOLTS (Job Openings and Labor Turnover Survey).[3] In addition to detailed information on occupation, geography, and employer for each vacancy, BGT data contain thousands of specific skills standardized from open text in each job posting. BGT data thus allow for a detailed analysis of vacancy flows within and across occupations, firms, and labor market areas, enabling us to document trends in employers' concentration at a very granular level.

The data, however, is not perfect. Although roughly two-thirds of hiring is replacement hiring, we expect vacancies to be somewhat skewed towards growing areas of the economy (Lazear and Spletzer, 2012; Davis, Faberman and Haltiwanger, 2012). Additionally, the BGT data only covers online vacancies. Even though vacancies for available jobs have increasingly appeared online rather than in traditional sources, it is a valid concern that the types of jobs posted online are not representative of all openings. Hershbein and Kahn (2018) provide a detailed description of the industry-occupation mix of vacancies in BGT relative to JOLTS: although BGT postings are disproportionately concentrated in occupations and industries that require greater skill, the distributions are stable across time, and the aggregate and industry trends in BGT track BLS sources closely.

Finally, it is worth noting that not every job posting in the data contains a valid entry for every possible field. For example, not all job ads report the employer name.[4] We restrict our sample to ads that contain valid values for employer name, employer location, industry, and occupational codes. This restriction drops about 40 percent of postings — most on account of missing employer name. We also restrict our sample to firms that posted at least 5 ads per year. These firms are labeled as "active" in the labor market).[5]

3.2 LBD

Online vacancy data from BGT, though comprehensive in their sectoral and geographic coverage, may underrepresent jobs that are not posted online. Furthermore, BGT data have a limited time series dimension. For this reason, we turn to the Census Bureau's Longitudinal Business Database

[3] Although JOLTS asks a nationally representative sample of employers about vacancies they wish to fill in the near term, the data are typically available only at aggregated levels, and do not allow for a detailed taxonomy of local labor markets.

[4] In many cases, these are "true" missings in that the text of the original posting made no mention of the employer name. BGT makes the original text of the job postings it spiders available, so we can confirm this pattern in a random subsample of the data. We suspect many of these job ads are posted by temporary help and staffing firms.

[5] We explored the sensitivity of our results to bounding assumptions on posts lacking an employer name, or the requirement that active firms post at least 5 ads per year; the results are not sensitive to these restrictions.

(LBD), a yearly administrative dataset covering the universe of non-farm private jobs in the U.S. since 1976. A product of the Census Bureau, the LBD reliability for computations of employment and job dynamics are unparalleled (Jarmin and Miranda, 2002). Importantly, the LBD provides longitudinal firm identifiers that enables us to study the evolution of firm-level employment over time.

We use the LBD to compute three measures of labor utilization: the stock of employment, job creation flows, and total payroll at the yearly frequency. The LBD also offers detailed industry and geography descriptions, so that we can ascribe firm-level outcomes to specific local labor markets depending on the sector and geography in which the firm is active. If a firm has establishments in more than one sector or geography, we deem it "active" in all of them and compute its contribution to total employment or job flows accordingly.

3.3 Local labor markets

We characterize a local labor market as a sector-location pair in each year. In the BGT data, we define a local labor market as an occupation-metro area pair in each year. Information on occupation and metro areas is not standardly available in the LBD data, so we define a local labor market as an industry-county pair. Our results are robust to defining local labor markets in the LBD as an industry-metro area pair, but details are pending disclosure.

We define occupations at the 4-digit SOC level, for a total of 108 groups derived from the Bureau of Labor Statistics 2010 SOC system, which aggregates "occupations with similar skills or work activities" (BLS, 2010). While our definition of occupations is considerably less detailed than the job titles available in the BGT data, we believe it offers an appropriate balance between accurately capturing the competitiveness of a market and identifying the demand for different bundles of skills.[6] Nevertheless, our results hold true for other classifications. Examples of SOC 4-digits occupations among Production ones are Food Processing Workers (5130), Assemblers and Fabricators (5120), Textile, Apparel, and Furnishings Workers (5160), and Plant and System Operators (5180)

The LBD is an establishment-level data set and does not contain information on specific occupations within each establishment. We, therefore, shift our analysis to industries and utilize the time-consistent NAICS classification as developed by Fort and Klimek (2018). Our main results

[6] Indeed, too fine an occupational classification would mechanically lead to a small number of firms posting jobs in each market. This would bias our estimates of labor market concentration upward. On the other hand, too broad an occupational classification would erase important distinctions between heterogeneous skills used in different occupations. As much literature finds that broad occupational change are not uncommon in the U.S. labor markets, especially for laid-off workers, we choose the 4-digit SOC level as a useful compromise (Huckfeldt, 2017; Macaluso, 2017).

use 3-digit NAICS codes for a total of more than 200 distinct industries. We think that the 3-digit NAICS classification aligns well with our preferred 4-digits SOC classification of occupations in BGT data, but we verify that our results hold true for other classifications. Examples of 3-digit NAICS industries among the manufacturing ones are Food Manufacturing (311), Beverage and Tobacco Product Manufacturing (312), Textile Mills (313), and Apparel Manufacturing (315).

Metropolitan areas correspond to the 2013 Core-Based Statistical Areas (CBSA) with a population over 50,000. As a result, there are 382 metro areas in our final BGT dataset. We concentrate on urban labor markets for a few reasons. First, there is evidence more than 80% of job seekers apply to job openings in their same metro area of residence (Marinescu and Rathelot, 2018), so a CBSA appears to be a meaningful definition of *local* labor markets for most workers. In addition, since in rural areas it is not unusual to have only a few employers in each labor market, we elect to study labor market concentration in urban settings to avoid the natural correlation between rural status and the level of labor market concentration. On the other hand, the metropolitan areas classification is not native to the LBD data; therefore, we choose to approximate it with counties with at least 75,000 employed workers.[7] There are more than 1,000 counties that satisfy this requirement in the U.S. as per the 2013 Census delineations.

As a result of our definition of local labor markets, we identify 41,256 local labor markets in BGT and more than 25,400 in the LBD, observed at the yearly frequency. We restrict our sample to civilian jobs only with the additional restriction that occupation/industry and location are non-missing. Furthermore, we exclude those locations from our sample that are not in the continental U.S.

In BGT data, the average market has 277 job postings per year, but 50% of the markets have fewer than 34: the distribution of postings is highly skewed to the left. A similar result is reflected in the number of active employers, i.e. firms that post at least 5 jobs per year in any market: while the average number of active employers per market is 30, the median is 7. When we look at the stock of employment in the LBD, we find more limited skewness. The average number of jobs in each market-year cell in the LBD is 14,300 and the median 13,500, distributed among an average of 28 employers (median, 29).[8] Summary statistics for job creation and payroll are awaiting disclosure.

[7]The Census Bureau defines metropolitan areas as those urban areas with at least 100,000 residents, and micropolitan areas as those urban (and suburban) areas with at least 50,000 residents. Applying an average employment-to-population ratio of 75%, we feel confident that including only counties with 75,000 employees exclude most rural counties, and guarantees an "apples-to-apples" comparison between BGT and LBD data.

[8]Numbers are rounded as per the Census Bureau's disclosure rules.

4 Trends in labor market concentration

4.1 National and local concentration in output and input markets

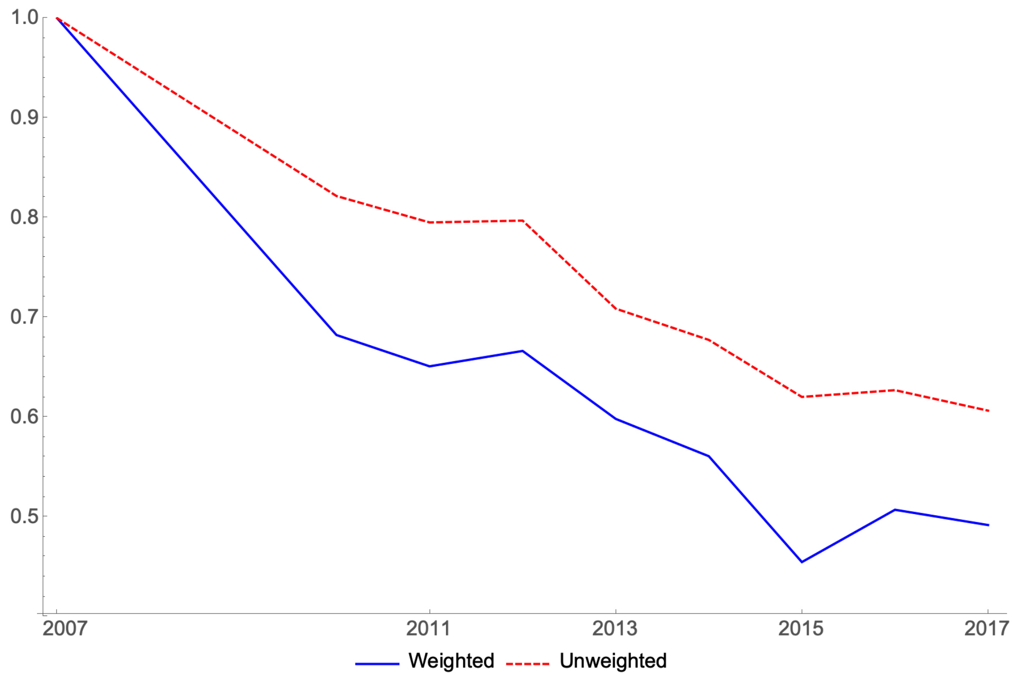
VACANCIES. We regard vacancies concentration as the closest measure to the concentration faced by job seekers in a specific local (national) labor market. We construct concentration measures of vacancies (job postings) following (2) and (4) and using BGT data. Market-level HHIs are aggregated through their respective vacancy shares. Figure 1 plots the time series of the aggregate local concentration of vacancies and shows that local concentration is markedly decreasing over time. Specifically, the local HHI of vacancies drops in the post recession period 2010–2017 by approximately 20%. The decrease is even more dramatic if we consider the change between 2007 and 2017 — though it is to be noted that the BGT data is not available during 2008-09. Figure 1 also displays a measure of local concentration in which each market is equally weighted. Using this "unweighted" measure does not change the aggregate trend in the concentration of vacancies as per BGT data. This observation suggests that the decline in local concentration is not purely driven by market composition effects.

One concern is that the displayed aggregate trend in the BGT data reflects either the post-recession recovery in job creation or advances in technology that allow BGT to capture a larger number of vacancies over time. However, we alleviate these concerns in the following subsection by showing that the HHI of employment, computed from Census data starting in 1976, has also decreased over time.

EMPLOYMENT. In the figure below, we construct national and local concentration measures for employment. Employment also functions as the size of a market and markets are thus aggregated through employment shares. As can be seen in figure 2, we find that local employment concentration displays a strong declining trend: it has declined by 28% over the period 1976–2014. Most of the decline occurred between the 1980s and the mid 1990s. Though there is a small uptick during the 2007–08 recession, it appears small with respect to the overall trend. The declining trend in local employment concentration corroborates our previous result on vacancies. We conclude that local labor market concentration does not only decline in terms of vacancies over the relatively short period of 2007–2017, but also when we consider the stock of employment from 1976–2014.

Unlike the vacancy series in the BGT data, the 1976–2014 change in the LBD for local concentration with equalized weights across markets is a mere -2%. Specifically, the series for the unweighted HHI of employment in the LBD displays a weak U-shape with its minimum in the mid-1990s. Concentration declines by about 5% until 1994, and then increases by 2.5% between 1995

Figure 1: National and local trends in the concentration of job postings. Source: BGT.



(a) BGT (2007, 2010–2017). HHI levels are normalized relative to their initial value in 2007.

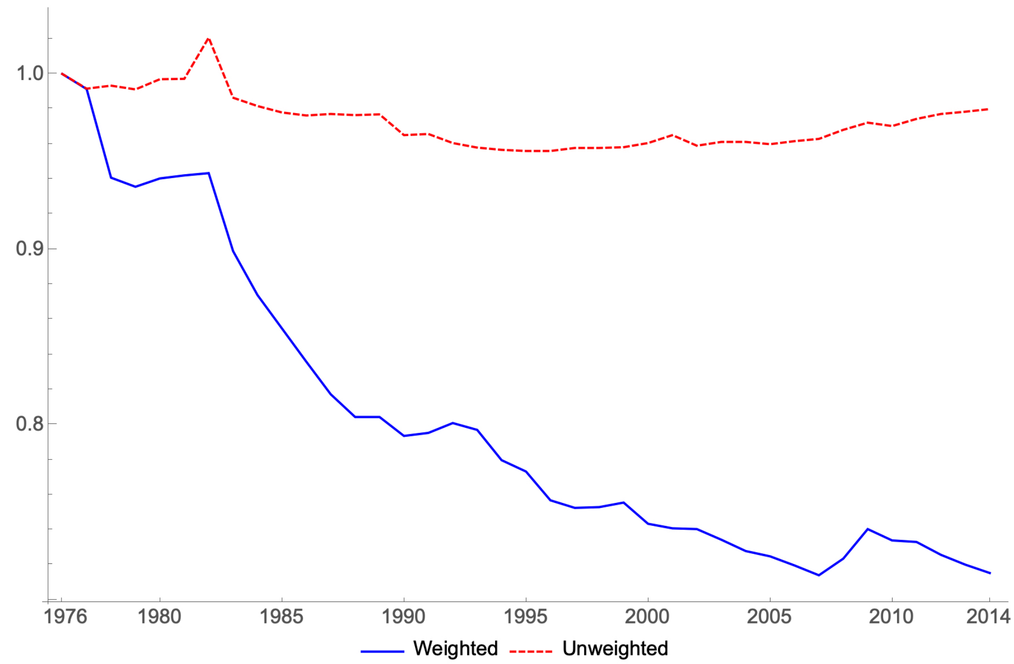
and 2014. The overall trend is still negative, though much less markedly so than in the weighted series.[9]

The difference between the weighted and unweighted trends for local employment concentration is due to differential trends in sparsely populated and manufacturing-intensive markets. In addition, the unweighted trend in employment concentration has the same qualitative features of a series of employment concentration computed as if the whole U.S. economy was a single labor market. Finally, the series for job creation and payroll have the same qualitative features as the one for employment, though details are pending as we are awaiting disclosure.

Our results on unweighted employment concentration mirrors the results on national concentration sales in Autor et al. (2017). In both series there is a clear increasing trend from the mid 1990s onward. At the same time, our measure for *local* employment concentration seems to be consistent with the evidence on local sales concentration presented in Rossi-Hansberg, Sarte and Trachter (2018). We conclude that there is a diverging trend between national and local employment concentration, similar to what is observed in national and local sales concentration. While this seems contradictory at first sight, we argue in section 4.3 that such patterns can be rationalized through a

[9]The artificial spike in 1982 is due to an anomalous high rate of entry for firms in agriculture. This change seems spurious and is most likely an artifact of reclassification error.

Figure 2: Trends in the concentration of employment. Source: LBD.



(a) LBD (1976–2014). HHI levels are normalized relative to their initial value in 1976.

declining relationship between market size and concentration at the local level.

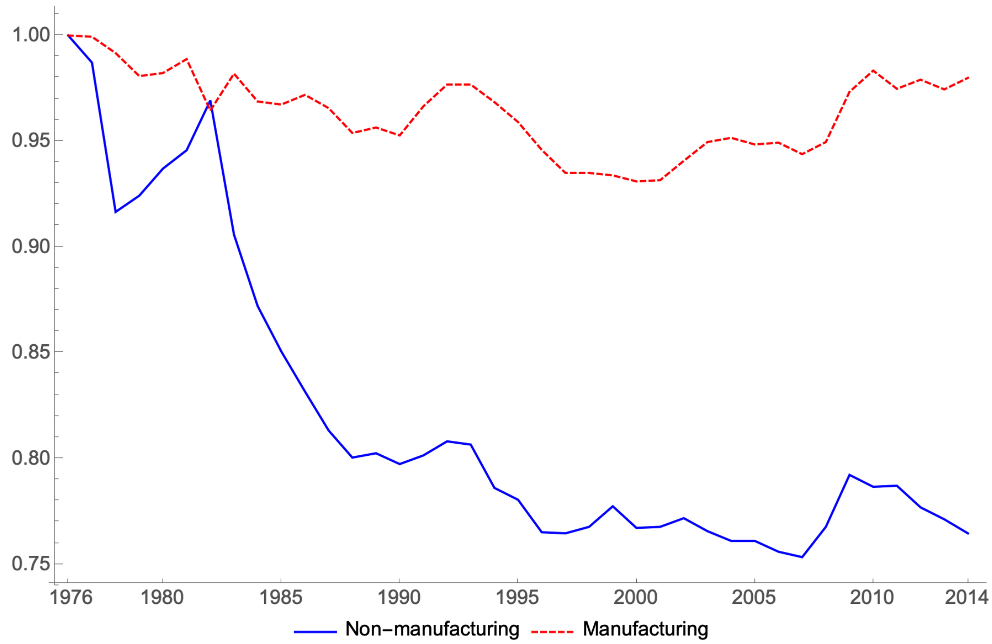
4.2 Industry-specific trends

The decline in labor market concentration shown in the previous section is common to most industries and geographies, but there is a substantial heterogeneity across sectors. Namely, we find that manufacturing markets deviate substantially from the average characterization. In fact, the manufacturing sector displays a higher level of concentration than other industries, and concentration has been increasing at least since the early 2000s. This is depicted in figure 3, in which we split the sample in manufacturing and non-manufacturing markets. Manufacturing market are on average more concentrated than non-manufacturing ones and concentration has not declined as much as in other sectors.[10] Specifically, while non-manufacturing markets have experienced a decline in employment concentration of at least 25% since the late 1970s, manufacturing ones saw a relatively mild decline until the mid 1990s and an increase afterwards. We conclude that any attempt to extrapolate the overall effects of labor market concentration from data on the manufac-

[10]Figure 3 only plots a normalized trend, but the average HHI level in manufacturing fluctuates between 0.32 and 0.35 from 1976–2014. This is in stark contrast with non-manufacturing industries whose average HHI level fluctuates between 0.15 and 0.20.

turing sector must take into account the difference between the level and growth of concentration in manufacturing and non-manufacturing markets.

Figure 3: HHI of employment for manufacturing and non-manufacturing markets from 1976 - 2014. Source: LBD.



(a) LBD (1976–2014). HHI levels are normalized relative to their initial value in 1976.

4.3 Reconciling national and local trends

In the previous section, we computed the time series for several measures of labor market concentration — the HHIs/ CRs of employment, job creation, payroll, and vacancy flows — and find that national labor market concentration has not increased, while local labor market concentration has diminished substantially since the late 1970s. The available evidence on secular trends in sales concentration illustrates a similar divergence in trends between national and local measures. Specifically, Autor et al. (2017) show that various measures of national sales concentration have been trending *upward* in most industries since the beginning of the 1980s. In contrast, Rossi-Hansberg, Sarte and Trachter (2018) find that local sales concentration in the NETS database has been trending *downward* since 1990. Rinz (2018) also emphasizes the diverging trend(s) between national and local employment concentration.

While these empirical facts seem contradictory at first, we show that they are not. In fact, we derive a condition on the relationship between the size of a local market and its concentration level that would reconcile these diverse findings. To do so, we employ a statistical decomposition based on Olley and Pakes (1996) and directly relate aggregate local concentration to its national counterpart. Following Rossi-Hansberg, Sarte and Trachter (2018), we define aggregate local concentration as a weighted average of HHI measures across different industry-region cells. Note that the following decomposition does not make any assumptions on the granularity of these cells or the nature of the weights. Furthermore, we define national concentration as a weighted average of HHI measures across industries, as in Autor et al. (2017).

Let j, ℓ and t denote industries, locations and years, respectively. Then, aggregate local concentration can be decomposed as follows:

$$
\begin{aligned}
\underbrace{\sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} HHI_{j\ell t}}_{=\text{LOCAL}_t} &= \sum_{j \in J} \omega_{jt} \left[\sum_{\ell \in L} \frac{\omega_{j\ell t}}{\omega_{jt}} HHI_{j\ell t} \right] \\
&= \sum_{j \in J} \omega_{jt} \left[\sum_{\ell \in L} s^j_{\ell t} HHI_{j\ell t} \right] \\
&= \sum_{j \in J} \omega_{jt} \left[\overline{HHI}_{jt} + cov(s^j_{\ell t}, HHI_{j\ell t}) \right] \\
&= \underbrace{\sum_{j \in J} \omega_{jt} HHI_{jt}}_{=\text{NATIONAL}_t} + \sum_{j \in J} \omega_{jt} cov(s^j_{\ell t}, HHI_{j\ell t}) - \sum_{j \in J} \omega_{jt} (HHI_{jt} - \overline{HHI}_{jt})
\end{aligned} \tag{9}
$$

where $\overline{HHI}_{jt} \equiv \frac{1}{|L|} \sum_{\ell \in L} HHI_{j\ell t}$ is the unconditional mean of HHI across locations in a given industry j and year t. According to this decomposition, aggregate local concentration LOCAL_t can be thought of as the sum between (i) national aggregate concentration NATIONAL_t, (ii) the employment-weighted covariance between the share of a local labor market in industry-level employment and the market's local concentration level, and (iii) a residual term capturing deviations of industry-level HHI's from unconditional averages. Then, diverging trends between national and local aggregate concentration (based on HHI) can be rationalized through (i) a declining covariance between market size and concentration at the local level and/or (ii) smaller deviations of industry-level HHI's from unconditional averages. These conditions would be verified, for example, if larger local labor markets became less and less concentrated over time or the dispersion in industry-level concentration had declined. In work in progress, we provide evidence to support these hypotheses, estimating each component in decomposition (9) and illustrating their time trends.

4.4 Employment versus sales concentration

The previous sections illustrate how there is no evidence in job and vacancy data pointing to an increase in labor market concentration; in fact, we find that labor market concentration has declined in the last four decades. However, the magnitude of this decline depend on whether one studies the national or local series. This difference, which we have shown can be rationalized if larger local labor markets have become less and less concentrated over time, mirrors closely a similar divergence between local and national concentration in sales. For this reason, we now explore how concentration in the output market relates to concentration in the labor market. In the next section, we provide a set of sufficient conditions under which the HHI for these two variables coincide.

Assume a generalized monopolistically competitive environment akin to Arkolakis et al. (2017). We do this to ensure that our results do not hinge upon specific demand structures. There is a continuum of goods which are indexed by $\nu \in \Omega$ with prices $\mathbf{p} = \{p(\nu)\}_{\nu\in\Omega}$. A given consumer with income I has Marshallian demand for some good $\nu \in \Omega$ equal to:

$$q_\nu(\mathbf{p}, I) = Q(\mathbf{p}, I) D\left(\frac{p(\nu)}{P(\mathbf{p}, I)}\right) \tag{10}$$

where $Q(\mathbf{p}, I)$ is a demand shifter and $P(\mathbf{p}, I)$ reflects an aggregate price index. Arkolakis et al. (2017) introduce a system of equations that jointly solve for $Q(\mathbf{p}, I)$ and $P(\mathbf{p}, I)$. In doing so, they create a setup that is rich enough to encompass a wide variety of demand systems such as CES, additively separable (but non-CES) utility functions (as in Krugman, 1979), symmetric translog expenditure functions (see Feenstra, 2003), quadratic mean of order r (QMOR) expenditure functions (as in Feenstra, 2018) and Kimball preferences (see Kimball (1995) and Klenow and Willis (2016)).

Firms are endowed with a linear production technology in labor only and heterogeneous in their level of productivity z_i. Labor is compensated at the common wage rate w. Obviously, this assumption is not applicable in the specific context of this paper, but it is often assumed in models of firm dynamics and trade that labor is perfectly mobile within a market. The point here is to demonstrate what additional assumptions are required in commonly specified environments to establish a tight link between sales and employment HHIs.

Due to our assumption of perfectly mobile labor within a market, a firm's marginal cost of production is given by $c_i = w/z_i$. For the moment, we drop firm indices to simplify notation. Then, a firm's profit maximization problem is given by:

$$\max_{p \geq 0} (p - c) Q(\mathbf{p}, I) D\left(\frac{p(\nu)}{P(\mathbf{p}, I)}\right)$$

Following Arkolakis et al. (2017), we define a firm's market-specific relative efficiency as $v = P(\mathbf{p}, I)/c$. A firm's optimality condition is then implicitly characterized by:

$$\begin{aligned} \mu &= \frac{p}{c} \\ &= \frac{\varepsilon_D\left(\frac{\mu}{v}\right)}{\varepsilon_D\left(\frac{\mu}{v}\right) - 1} \end{aligned} \tag{11}$$

where μ denotes a firm's price-cost markup. This immediately implies that a firm's sales (or revenues) and labor demand can be written as:

$$\text{rev}(v) = Q(\mathbf{p}, I) c \mu(v) D\left(\frac{\mu(v)}{v}\right) \tag{12}$$

$$\text{emp}(v) = Q(\mathbf{p}, I) D\left(\frac{\mu(v)}{v}\right) \frac{c}{w} \tag{13}$$

Therefore, a market's HHI for sales and employment are equal to the following expressions:

$$HHI^{\text{rev}} = \sum_{\nu \in \Omega} \left(\frac{\frac{\mu(v)}{v} D\left(\frac{\mu(v)}{v}\right)}{\sum_{\nu' \in \Omega} \frac{\mu(v')}{v'} D\left(\frac{\mu(v')}{v'}\right)} \right)^2 \tag{14}$$

$$HHI^{\text{emp}} = \sum_{\nu \in \Omega} \left(\frac{\frac{1}{v} D\left(\frac{\mu(v)}{v}\right)}{\sum_{\nu' \in \Omega} \frac{1}{v'} D\left(\frac{\mu(v')}{v'}\right)} \right)^2 \tag{15}$$

The above expressions imply that generally we have $HHI^{\text{rev}} \neq HHI^{\text{emp}}$. It is immediately clear from expressions (14) and (15) that we must have $HHI^{\text{rev}} = HHI^{\text{emp}}$ if and only if markups are equalized across firms in a given market. This is achieved whenever preferences are of the CES form.

5 Local labor market concentration in the cross-section

Section 4 shows that the data provides little evidence for a secular increase in labor market concentration; if anything, we find a robust decline in local concentration since the late 1970s. In this section, we move on to analyze the cross-sectional properties of concentration in employment, job creation, and vacancies. The main take-away is that we do not find evidence of widespread concentration in employment or job and vacancy flows. On the other hand, we also show that concentrated markets are small and their employer mix is skewed toward large national firms that are active across multiple regions.

Table I: Summary statistics for local labor market HHI.

	Job postings (BGT)	Employment (LBD)
Mean	0.0571	0.1825
Median	0.0272	0.0774
25th pct	0.0117	0.0216
75th pct	0.0591	0.2389
SD	0.0930	0.2417

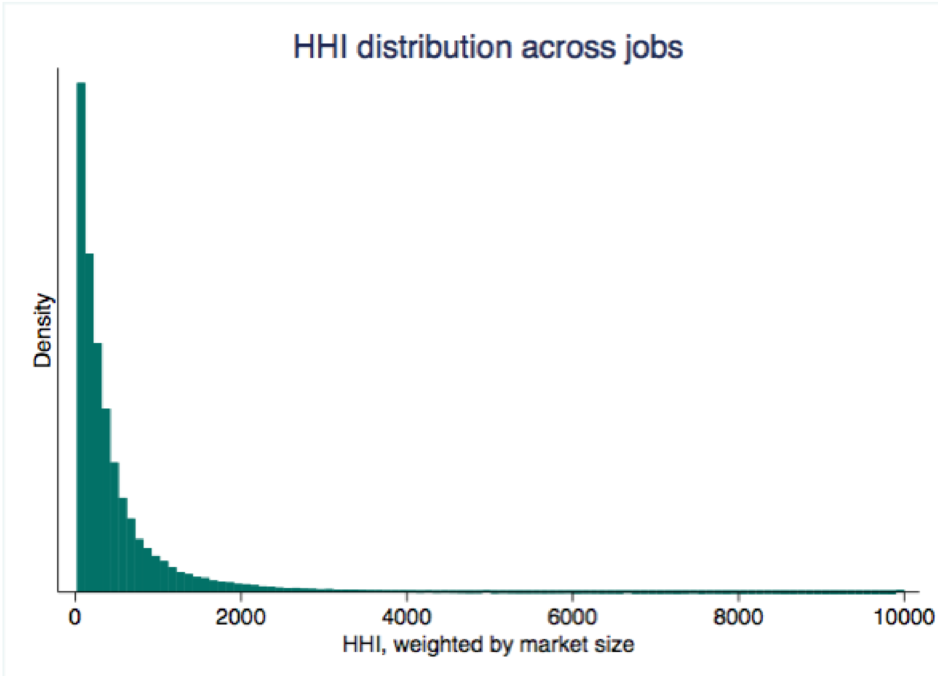
Employment stock is more concentrated than job postings flow, but only markets above the 75^{th} percentile are "moderately concentrated" according to DOJ guidelines (HHI > 0.25). All markets are weighted by their size. The results for job creation and payroll in the LBD are pending disclosure. Source: BGT, LBD.

Table I reports summary statistics for the HHI of various measures of labor utilization. The employment stock (LBD) is, on average, more concentrated than the flows of job postings (BGT). However, only labor markets above the 75th percentile are "moderately concentrated" according to DOJ guidelines applied to the employment HHI from LBD data.[11] The concentration of vacancy flows, on the other hand, is modest across the board. In BGT, only 5% of vacancies in the post-recession period is in a moderately concentrated market. To see this in further detail, figure 4 depicts the full distribution for the HHI of job postings. The figure has two panels: in the top one, we report the *weighted* distribution of the HHI of vacancies where weights are equal to market size, i.e. the total number of job ads in a market-year cell. In the bottom panel, we present the same distribution but without using the weights. The difference in the size of the right tails tells us that the most concentrated markets are also the smallest in terms of vacancy creation. Analogous figures can be constructed from the LBD employment and job creation variables.

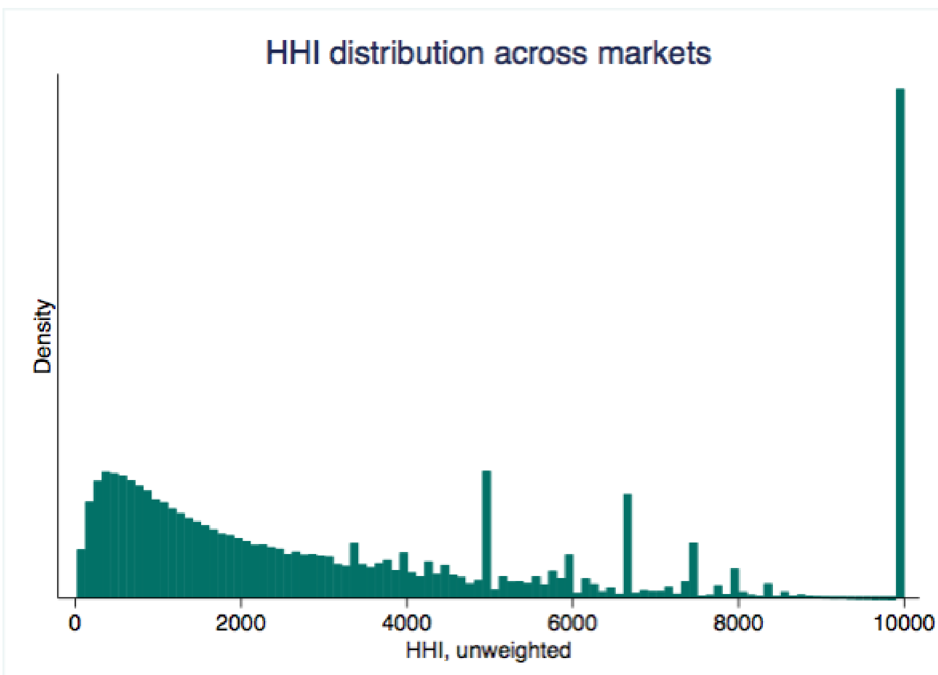
To further show that concentrated markets tend to be small, consider that the number of postings per year is negatively correlated with the level of concentration. Table II displays statistics from

[11] The official threshold for concentrated markets in the product market is a HHI of sales greater or equal than 2500.

Figure 4: Local HHI distribution of job postings from 2007 - 2017. Source: BGT.



(a) Weighted by market size



(b) Unweighted

BGT and LBD that illustrate this result: in first row of the top panel, we compute the total number of postings per year by quartiles (terciles) of vacancy (employment) concentration. Markets in the highest concentration quantiles post on average 23 jobs per year, in contrast with 596 job ads per year in the least concentrated markets.

We also find that the employer mix in concentrated markets is skewed toward nationally large firms. In other words, firms that are active in concentrated markets tend to post more jobs and employ more workers *across all markets* than those who are active in more competitive markets. This can be seen in the second row of table II where we calculate the average number of postings in all markets (that is, in all locations and for all occupations) for firms active in each quartile of the labor market concentration distribution. We conclude that the relationship between firm-level job postings volume and labor market concentration is positive. The average employer who posts jobs in a labor market above the 75th concentration percentile advertises for 173 jobs in a year while the average employer who posts jobs in a labor market below the 25th concentration percentile advertises for 84 jobs in a year; about half as many. Local branches of these employers are not necessarily larger however: the number of postings per employer–metro-area–year does not vary with labor market concentration (row 3 in table II). These patterns hold true both for employment as well. Indeed, the positive relationship we found between the level of labor market concentration and the volume of job postings holds also in terms of firm-level employment (as seen in the second panel of table II). Specifically, we find that firms in concentrated markets employ more workers over all markets than firms in competitive markets do. Patterns for job creation, for which we are awaiting disclosure, are consistent with the findings for employment and job postings. We interpret this evidence as suggestive of the fact that firms active in more concentrated local labor markets tend to be larger *on a national scale*, and that less concentrated markets have a greater number of smaller firms instead. At the same time, another robust finding is that most concentrated markets are small and most jobs/workers are not in a concentrated market.

Table II: Concentrated markets are small and their employer mix is skewed toward nationally large firms. Source: BGT, LBD.

	Market's rank in vacancy HHI distribution (BGT)			
Vacancies per	1st quartile	2nd quartile	3rd quartile	4th quartile
market-t	596	171	77	23
firm-t	**84**	125	155	**173**
firm-MSA-t	5	5	5	5

	Market's rank in employment HHI distribution (LBD)		
Jobs per	1st tercile	2nd tercile	3rd tercile
market-t	3200	450	200
firm-t	<**15**	20	**30**
firm-county-t	<15	<15	<15

6 Labor market concentration, skills, and wages

In this section, we analyze how the *macro*-structure of local labor markets — how concentrated they are and the shape of their firm size distribution — affects the *micro*-structure of labor markets. We start with the relationship between local labor market concentration and the level of wages. We show that the overall correlation is negative but small in magnitude. Then, we study how labor market concentration correlates with the skill content of jobs, in order to disentangle the effects of potential employer market power on both the quantity and quality of labor. We find that skill requirements of jobs are increasing in local labor market concentration, even within narrow occupations, and also when we restrict ourselves to within-firm variation. In other words, the same firm posting a job into two different markets, one with low and one with high concentration, tends to include more skill requirements in the job ad that is active in a concentrated market than in the job ad in the more competitive market. We refer to this phenomenon as "upskilling", and to the negative association between wages and concentration as "wage compression".

6.1 Wages

We follow the literature in estimating the relationship between wages and local labor market concentration by adopting the following specification:

$$\log \bar{w}_{mt} = \mu + \gamma \log(HHI_{mt}) + \mathbf{X}'_{mt}\beta + \varepsilon_{mt}$$

We run our specification at the market-year level using average wages for occupation-metro area cells from the Occupational Employment Statistics (OES). The OES data is particularly well-suited to our purposes, because it is derived from establishment-level data and is less prone to measurement error than household data. We use the HHI of vacancies from BGT as our main regressor, and include a rich set of fixed effects at the occupation, city and year level. In addition, we use market size (i.e., total number of ads) as a market-year control. Standard errors are clustered at the market level.

As depicted in table III, we find an elasticity of wages to concentration between -0.01 and -0.05. In our preferred specification, in column (2), we find that a one percent increase in the concentration of job postings is associated with 0.1% decline in the average local wage. Results for the median level of wages are virtually identical. This elasticity is relatively small, but consider that, as can be seen in column (1), it is about a third of the elasticity of wages to city size (proxied by labor force), and a tenth of the elasticity to the local share of college educated workers (denoted by college share). Both city size and college share are well-investigated source of agglomeration in wages

Table III: Labor market concentration is negatively correlated with the average level of wages.

	(1)	(2)	(3)
log(HHI)	**-0.012**	**-0.014**	**-0.050**
	(10.99)	(7.43)	(9.97)
$\log(\text{HHI})^2$	–	–	0.003
			(7.67)
log(labor force)	0.031	–	–
	(7.39)		
log(college share)	0.146	–	–
	(8.64)		
log(unempl. rate)	0.036	–	–
	(6.69)		
Occupation FE	✓	✓	✓
Year FE	✓	✓	✓
MSA FE	–	✓	✓
N	371,304		

(Moretti, 2010). In addition, a one standard deviation increase in the vacancy HHI is equal to a 80% change with respect to the mean and would translate in approximately a 1% decline in the average hourly wage (0.14 cents in 2017). To conclude, we believe that the negative association between average wages and labor market concentration is economically meaningful, even though we find a magnitude that is somewhat smaller than previous studies.

In particular, our estimates are similar in magnitude to Benmelech, Bergman and Kim (2018), while the elasticities in Azar, Marinescu and Steinbaum (2017) are much larger than what we find. This is perhaps unsurprising, as we investigate the relationship between labor market concentration and *realized* wages, while the former study focuses on *posted* wages. Both margins are relevant: the large negative association between posted wages and concentration highlighted in Azar, Marinescu and Steinbaum (2017) underlines how the initial bargaining position of employers changes as a result of their competitive position in the local labor market. Our finding, on the other hand, confirms that the relationship between concentration and realized wages is negative, but smaller in magnitude. This suggests that general equilibrium forces tend to attenuate employers' market power or that such power influences the marginal worker more than the average worker.

6.2 Skills

When interpreted at face value, the negative correlation between labor market concentration and the average level of wages suggests that employers in concentrated market enjoy some degree of monopsony power. While the debate on this issue is still open in the literature, we turn our attention to another margin that is potentially affected by labor market concentration. Indeed, the *quantity* of labor is not the only variable that an employer with monopsony power can affect: when workers are heterogeneous, employers also choose the labor mix, that is, the *quality* of labor. Is there evidence that firms in more concentrated market demand more skilled workers, even within narrow occupational categories? In this section, we provide an answer to this question using the rich skill data in BGT.

We find that the skill content of jobs is positively correlated with labor market concentration. We conclude that, taken together, our evidence on wage compression and upskilling is consistent with the presence of employers' market power. The presence of upskilling effects, however, poses significant challenges for policy. Indeed, the negative effect of monopsony on the level of wages is a popular justification for increases in the minimum wage at least since Card and Krueger (1994). However, our result on the positive relationship between concentration and upskilling points out that the effects of monopsony on the labor market are not limited to lower wages and, as such, are unlikely to be neutralized by a minimum wage hike.

6.2.1 A taxonomy

To study the skill content of jobs as a function of concentration, we exploit five categories of skill requirements in the BGT data, utilizing the stated demand for skills that we classify as cognitive, social, and organizational, and stated demand for computer skills, either general or specialized.[12] These skill requirements represent a broad swath of human capital measures in which employers are interested. In addition, this particular categorization follows the approach adopted in previous literatures (Autor, Levy and Murnane, 2003; Brynjolfsson and McAfee, 2011; Deming, 2017; Deming and Kahn, 2018; Hershbein and Kahn, 2018).

We categorize skill requirements based on the presence of keywords in the open text fields for skills. For example, if the job posting calls for "Multi-tasking" and "People skills", we would classify it as requiring both organizational and social skills. The keywords we use to define cognitive, social, and organizational skill requirements follow Deming and Kahn (2018) and Hershbein and Kahn (2018), and closely match the analysis in Autor, Levy and Murnane (2003). More specifically, we define a job post to require social skills if any of the keywords "communication," "presentation," "collaboration," "negotiation," "team," "listening," or "people skills" are present. We define cognitive skills if any of the keywords (or stems) "solving," "research," "analy," "decision," "thinking," "math,"

[12] We plan to add education and experience requirements, as in Hershbein and Kahn (2018), in the near future.

or "statistic" are present. And for organization skills, we code a positive if "organizational skills," "well organized," "detail," "tasking," "time management," "deadlines," or "energetic disposition" are present. For computer skills, we use a slightly different approach, as BGT already classifies this type of skill at different levels of specificity. We define a job post as requiring *general* computer skills if BGT classifies the post as having a computer skill or nonspecialized software skill (e.g., office productivity software). Similarly, we define the job posting as having *specialized* computer skills if BGT specifies specialized software (e.g., AutoCAD, Python, inventory management software).

Table IV: From 16,000 skill descriptors to 5 skill categories.

Skill group	Example key words
Social	Communication, presentation, collaboration, people skills
Cognitive	Solving, research, thinking, math, decision, analysis, analytical
Organizational	Well-organized, detail, tasking, deadlines, time management
Computer, general	Unspecified computer skills, common productivity packages
Computer, specific	Specialized softwares (e.g. AutoCAD, Python, C++)

6.2.2 Descriptive analysis: the skill content of jobs

We consider *stated* demand for various skills, and characterize firm-level skill demand in each market by counting how many job postings require each of the five skill categories we identified in the previous section: social, cognitive, organizational, specialized and general computer skills. For example, if firm f in market m posts 5 job ads, and one of them mentions both social and cognitive skills while two mention only social skills, we would describe firm f's skill demand in m by the vector (3 1 0 0 0). The elements of these vectors will be our main left-hand side variables in the empirical analysis. In other words, we use the number of firm-level ads mentioning each of the skill categories as our measure of local demand for skills by firms in each market. In doing so, we capture the extensive margin of skill demand within a given job posting, rather than the intensive margin, but the extensive is likely the more important margin. Many employer-market-year cells do not have any ads listing a specific skill category (see table V). That said, social skills are the most frequently requested while specialized computer skills are the least.

Table V: Stated demand for various skills (number of ads per firms), employers with at least 5 ads per year over the sample period (2007–2017).

Skill type	N	% of zeroes	Mean	Std. Dev.	Median
Social	15,032,577	49	0.892	3.360	0.200
Cognitive	15,032,577	59	0.661	3.092	0
Organizational	15,032,577	61	0.566	2.107	0
Computer, general	15,032,577	76	0.300	1.417	0
Computer, specific	15,032,577	95	0.066	1.202	0
Any computer	15,032,577	75	0.334	1.841	0

6.2.3 Labor market concentration and the demand for skills

Our first specification is a regression of the frequency of various skills in firm-level ads on the HHI (in natural logs) of the market in which the firm is active:

$$\text{\# mentions skill } \mathbf{s}_{fmt} = \mu + \gamma \log(HHI_{mt}) + \mathbf{X}'_{mt}\beta + \varepsilon_{fmt} \tag{16}$$

where f, m and t denote firms, markets and years, respectively. In addition to fixed effects for firm, occupation and year, we include a series of city-level controls to account for other determinants of local skill demand. Namely, we consider the size of the labor force, the share of young people (ages 18-25), the share of college-educated workers, and the local unemployment rate. All city-level variables except the local unemployment rate enter in natural log form and are taken from the 2000 Census to avoid endogeneity concerns and capture long-term differences, rather than short-term fluctuations, between metropolitan areas. The local unemployment rate is allowed to vary by year and is taken from the Local Unemployment Statistics. Standard errors are clustered at the market-year level.

We find that there is a large, positive association between local labor market concentration and the demand for skills, as illustrated in tables VI and VII. In table VI, we concentrate on social and cognitive skills. These are two skill categories for which demand has increased substantially in recent years (Deming, 2017; Deming and Kahn, 2018). The first and fourth columns report the results for our first specification equation (16), with all city-level controls at fixed in year 2000. As explanatory variables are in natural log terms, we can interpret the coefficients as semi-elasticities – i.e., an 1% increase in the HHI for a specific labor market increases the number of job postings that require social skills by 0.117 units. This effect is fairly large, as it represents 13% of the mean and 3.5% of the standard deviation (see table V). It is also half as large as the effect of a 1% increase in the share of the college-educated workforce and 40% as large as the effect of a 1% increase in the size of the local labor force. A similar story plays out for cognitive skills: a 1% increase in the

HHI for a specific labor market increases the number of job postings that require cognitive skills by 0.104 units. This represents 15% of the mean and 3.3% of the standard deviation, and is 60% as large as the effect of a 1% increase in the share of college-educated workforce and 48% as large as that of a 1% increase in the size of the local labor force.

Our results are robust to different specifications: in columns two/five and three/six of table VI we explore the sensitivity of our findings to (i) the inclusion of a control for market size — i.e., the total number of job ads in a metro area-occupation-year category; and (ii) the inclusion of metro area fixed effects alongside employer, occupation and year fixed effects. The coefficient on the concentration measure (γ) barely changes in these different specifications. Our preferred specification is an empirical model that is fully saturated with fixed effects. This includes fixed effects for employer, city, occupation, and year:

$$\text{\# mentions skill } \mathbf{s}_{fmt} = \mu + \alpha_f + \alpha_{o(m)} + \alpha_{c(m)} + \alpha_t + \gamma \log(HHI_{mt}) + \varepsilon_{fmt} \tag{17}$$

We use this specification to investigate how labor market concentration affects the demand for different types of skills. Figure 5 shows the equivalent of regression equation (17) in graphic form: on the y-axis, residualized skill demand for social (top) and cognitive (bottom) skills, and on the x-axis, the residualized HHI. The relationship is positive, well-approximated by a linear specification, and robust to the exclusion of duopsony and monopsony markets.

6.2.4 Labor market concentration for low- and high-skill jobs

In this section, we analyze the heterogeneous effects of labor market concentration for high- and low-skilled occupations. First, we show that the data does not support the hypothesis that low-skill labor markets are, on average, differentially concentrated than high-skill ones. Nonetheless, we find that the effect of labor market concentration on skill demand is indeed larger for low-skilled occupations.

High-skill labor markets are not necessarily more concentrated than low-skill ones. Indeed, the correlation between the average skill-level of an occupation and the average HHI across cities and years is small. As a first approach, we divide occupations into high- and low-skill, with SOCs in the 11–31 range constituting high skill and the remaining SOCs (33–53) constituting low skill.[13]

[13]The first group includes management; business/ financial; computer/ math; architecture/ engineering; physical/ social sciences; social services; legal; education; arts/ media; healthcare. The latter includes protective services; food preparation; cleaning/ maintenance; personal services; sales; office/ admin; farming/ fishing; construction/ extraction; installation/ maintenance; production; transportation.

Table VI: Demand for social and cognitive skills as a function of labor market characteristics. Standard errors clustered at the MSA-occupation-year level.

	social skills			cognitive skills		
log(HHI)	**0.101**	**0.104**	**0.117**	**0.064**	**0.064**	**0.070**
	(28.74)	(34.65)	(40.78)	18.97	21.37	26.47
log(labor force)	0.245	0.216	–	0.183	0.141	–
	(60.32)	(38.65)		(50.30)	(28.91)	
log(college share)	0.206	0.168	–	0.179	0.142	–
	(24.61)	(21.51)		(20.22)	(19.17)	
log(unempl. rate)	0.008	-0.040	–	0.015	-0.031	–
	(1.30)	(-6.73)		(2.60)	(-5.76)	
mkt size	–	0.0001	0.0001	–	0.0001	0.0001
		(8.49)	(8.46)		(8.72)	(8.72)
Employer FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	X	X	✓	X	X	✓
N	13,495,782	13,495,782	15,026,645	13,495,782	13,495,782	15,026,645
Unique employers	198,531	198,531	204,458	198,531	198,531	204,458
# clusters (MSA-SOC-year)	178,833	178,833	290,445	178,833	178,833	290,445

Note: t-statistics in parentheses

Table VII: Effect of concentration on demand for various skills: a 1% increase in the HHI raises the demand for cognitive skills almost 10 times more than the demand for specialized computer skills. Results are robust to the exclusion of high-concentration markets.

	Social		Cognitive		Organizational	
log(HHI)	0.117	0.115	0.070	0.068	0.077	0.076
	(40.78)	(38.65)	(26.47)	(24.60)	(36.82)	(35.19)
	Computer, general		Computer, specific		Any computer	
log(HHI)	0.049	0.048	0.018	0.017	0.060	0.059
	(31.97)	(30.30)	(4.34)	(4.05)	(15.32)	(14.35)
Employer FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
Excludes HHI≥5000	No	Yes	No	Yes	No	Yes
N	15,026,645					
Unique employers	204,458					
# clusters (MSA-SOC-year)	290,445					

Note: t-statistics in parentheses. Each coefficient is obtained from a separate regression.

When we correlate these binary skill indicators between 108 4-digit SOCs and the corresponding HHI, the Pearson correlation is 0.0632, and the Spearman (rank) correlation is 0.1255. We further investigate the importance of the composition effect by performing an unconditional regression at the firm-market-year level of HHI on a set of 22 2-digit SOC dummies. Consistent with the evidence from raw correlations, the relationship between the HHI and occupational categories is quite weak. Certain high-skilled occupation groups (scientists, education, health) tend to have concentrated labor markets, as do certain low-skilled occupation groups (protective and personal service, cleaning, construction, and production). Managers, business/finance, and computer occupations—all highly skilled—have low concentration, but sales, office support, and installation workers (low-skilled occupations) also tend to be in less concentrated markets. We conclude that there is no systematic evidence that the average skill-level of an occupation is correlated with its average labor market concentration.

However, the extent to which upskilling is associated with labor market concentration does vary with the average skill level of the occupation. Dividing the occupations into two skill groups as before, we return to equation equation (17) and allow the relationship between concentration and skill demand to differ between high-and low-skilled occupational groups. We find that the upskilling effect highlighted in table VIII is almost twice as strong for low-skilled occupations as for high-skilled ones. A 1% increase in the HHI of the local labor market increases the number

Table VIII: Effect of concentration on the demand for various skills: heterogeneity across occupations (low- vs. high-skilled).

	Social	Cognitive	Organizational
high-skill	0.081	0.045	0.061
	(19.36)	(11.10)	(24.84)
low-skill	0.131	0.093	0.064
	(36.99)	(27.10)	(28.65)
	Computer, general	**Computer, specific**	**Any computer**
high-skill	0.375	0.010	0.044
	(22.25)	(1.79)	(8.46)
low-skill	0.0397	0.026	0.057
	(20.20)	(5.70)	(12.39)
Employer FE	✓	✓	✓
Occupation FE	✓	✓	✓
Year FE	✓	✓	✓
MSA-level controls	✓	✓	✓
N	14,586,147	14,586,147	14,586,147
Unique employers	284,728	284,728	284,728
# clusters (MSA-SOC-year)	181,837	181,837	181,837

Note: t-statistics in parentheses.

of ads mentioning social skills by 0.131 units in low-skilled occupations and by 0.081 units for high-skilled ones, a difference of 60%. The differential effect of concentration on the demand for cognitive skills is even larger: 0.093 versus 0.045 additional ads, an increase of over 100%. However, this heterogeneity is present only for social and cognitive skills, not for other skill dimensions. In fact, the difference between the estimated HHI coefficients for low- and high-skill occupations, while positive, is not statistically significant for computer and organizational skills.

7 Conclusions

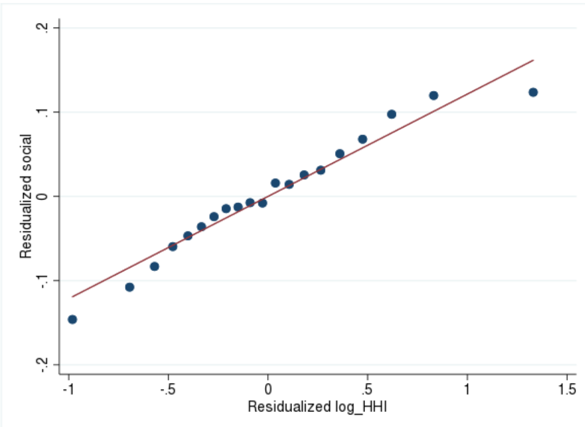
This paper characterizes the cross-sectional and time-series properties of concentration in employment, job creation, and vacancy flows across U.S. local labor markets. Our work has three main contributions: first, we derive conditions for indices of labor market concentration to be appropriate proxies for monopsony power. Specifically, we show that Herfindahl-Hirschman Indices of employment (or vacancy flows) are an accurate measure of monopsony power whenever the firm-level elasticity of labor supply is decreasing in firm size. The intuition behind this result stems from the idea that larger firms have a higher ability to compensate their workers below their marginal revenue if they face a lower labor supply elasticity than smaller employers. To verify this hypothesis, we propose an empirical strategy that exploits methods in the markup estimation literature and applies them to an environment with labor adjustment costs.

After having studied the condition for concentration indices to be valid measures of monopsony power, we compute Herfindahl-Hirschman Indices at the local labor market level. We use data on the universe of online vacancies (BGT) and the universe of employers (LBD), from which we compute employment stock, job flows and vacancy flows. We find that (i) in the last decade, at most 5% of new U.S. jobs are in moderately concentrated local markets; (ii) *local* labor market concentration decreased over time, dropping by at least 25% since 1976. We reconcile our findings to previous studies on increasing *national* concentration through a statistical decomposition which implies that the covariance between a local labor market's size and its concentration level decreased over time.

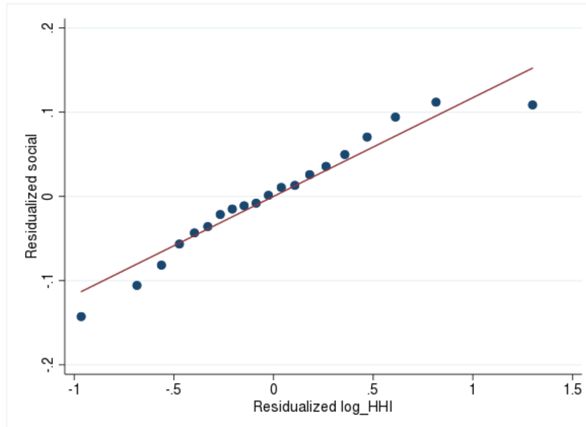
Using the HHIs and the rich information in both LBD and BGT data, we finally document that labor market monopsony does not manifest itself only through a negative effect on the level of wages, but also through a positive effect on the demand for skills. When it comes to the effects of monopsony, we find that a 1% increase in local labor market concentration is associated with a 0.14% decrease in average hourly wages, and also an increase in the number of jobs requiring cognitive and social skills equal to 10-13% of the mean. We conclude that our evidence is consistent with the presence of employers' market power and note how the upskilling effects we document constitute a policy challenge not readily addressed by increases in the minimum wage. While we recognize the cross-sectional effects of monopsony, we argue that the data provides little evidence of increased incidence of labor market concentration in the U.S.. Therefore, it is unlikely that labor market concentration accounts for the secular decline in labor market fluidity or the rapid increase in income inequality.

A Appendix

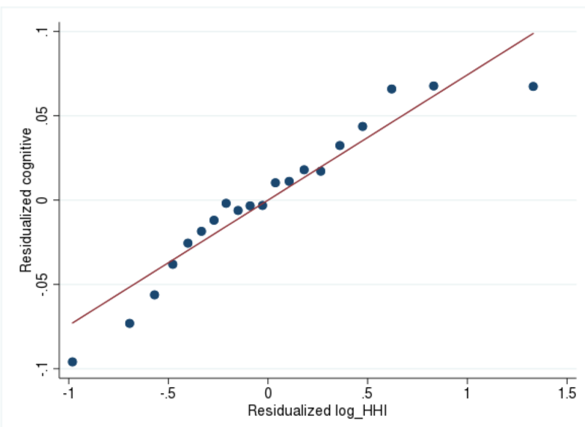
Figure 5: The positive relationship between labor market concentration and skill demand.



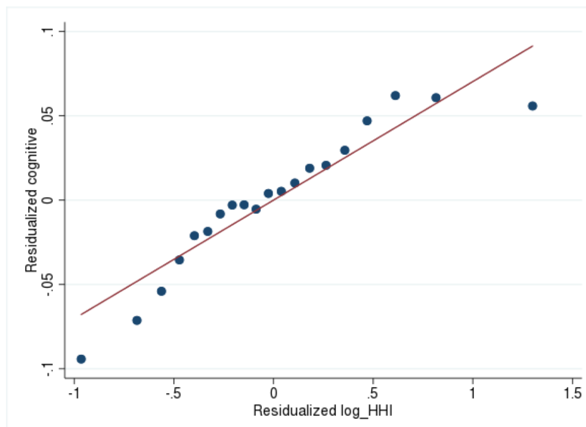
(a) Social skills (all markets)



(b) Social skills (markets with 3+ firms)



(c) Cognitive skills (all markets)



(d) Cognitive skills (markets with 3+ firms)

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