

# Labor Market Concentration and the Demand for Skills

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## Abstract

How is labor market concentration related to the skill content of jobs in a local area? In this paper, we bring novel, comprehensive data on job postings to this question, and show that (i) labor market concentration raises the skill requirements of jobs, even within narrowly-defined occupations; (ii) the largest increase in skill demand involves cognitive, social, and organizational skills; and (iii) the increase in skill requirements is larger for low-skilled occupations than for high-skilled occupations. These facts are not driven by markets with one or two employers, and are also present when we rely only on within-firm variation in labor market concentration. The increase in demand for skills associated with a 1% increase in local labor market concentration is substantial, and at least half as large as the effect of an increase of 1% in the local share of the college-educated population. We conclude that there is substantial evidence of upskilling in concentrated labor markets, and that our empirical findings are consistent with employers' market power.

## 1 Introduction

Large firms account for an increasingly large share of both employment and hiring in the U.S., and local labor markets on average display moderate to high concentration according to DOJ-FTC guidelines (Autor, Dorn, Katz, Patterson, and van Reenen, 2017; Decker, Jarmin, Haltiwanger, Miranda, 2016, 2017; Azar, Marinescu, and Steinbaum, 2017). At the same time, the returns to various skills have changed in recent decades, and there is evidence that technical change has favored cognitive and social skills over other types of human capital (Autor, Levy, Murnane, 2003; Deming, 2017; Deming and Kahn, 2017). However, it is not

known whether differences in the firm structure of labor markets are related to changes in the demand for various skills. How is labor market concentration related to the skill content of jobs in a local area? Do employers demand higher or lower levels of skill when searching for workers in a concentrated labor market? In this paper, we approach these questions using novel, comprehensive data on job postings. We find robust evidence for upskilling—i.e., a higher demand for skills—in concentrated labor markets. Specifically, we show that (i) labor market concentration raises the skill requirements of jobs, even within narrowly-defined occupations; (ii) the largest increase in skill demand involves cognitive, social, and organizational skills, with smaller increments in the demand for computer-related skills; and (iii) the positive effect of labor market concentration on skill requirements is larger for low-skilled than for high-skilled occupations. Our findings are not driven by markets with only one or two advertising employers, and remain unchanged after controlling for city size, the local share of the college-educated workforce, and the inclusion of firm-level and local area fixed effects. We place our findings into context by relating them to the literature on the negative effect of labor market concentration on the level of wages, and we conclude that our evidence on upskilling in concentrated labor markets is consistent with employers' market power.

This paper speaks to two significant changes that occurred during recent years in the U.S. labor market: (i) the rise in the share of employment at large firms, and (ii) the increase in returns to non-routine social and cognitive skills. Specifically, we ask whether these two phenomena are related through the effect of labor market concentration on the demand for skills.<sup>1</sup> First, we address the extent to which employer's market power is a prevalent phenomenon across U.S. local labor markets. We define local labor markets as metropolitan area-occupation-year cells. We measure concentration by calculating firm-level shares of job postings in each market and computing the Herfindahl-Hirschman index (HHI). We find that labor market concentration is a significant phenomenon: 30% of the local labor markets we consider have 3 or fewer employers advertising in a given year ( $\text{HHI} \geq 3,333$ ). Then, we show that the average firm in more concentrated markets posts more job ads across all markets than the average firm in less concentrated markets, which we interpret as indicating that firms in concentrated labor markets are on average larger than firms in more competitive markets. Finally, we investigate the demand for various types of labor as a function of local labor market concentration. We find robust evidence that labor market concentration is associated with an increased demand for skills, which is more pronounced for social and

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<sup>1</sup>Employers' market power can result in increased demand for skills in models with complementarities between firms' productivity and both the *quantity* and *quality* of workers, such as Garicano (2000) and Eeckhout and Kircher (2018), based on the classic span-of-control model by Lucas (1978).

cognitive skills.

To show how the demand for skill is related to employers' competitive position in the labor market, we use a unique dataset covering the near-universe of U.S. online vacancies in the years 2007 and 2010–2017. The data, collected by Burning Glass Technology (BGT), feature detailed descriptions of skill requirements for each posted position, including soft skills (“team player”, “good communicator”), cognitive abilities (“cost-benefit analysis”), general computer skills, and specialized software knowledge (“Python”, “C++”). Exploiting this rich set of information, we identify five categories of skills (social, cognitive, organizational, general computer, specialized computer) and characterize job ads by whether they mention these five skill categories. Aggregating to the firm-level, we document how firm-level demand for various skills changes as a function of the competitive pressure the firm faces from other employers in its local labor market.

Employers in markets with greater concentration, as measured by the HHI of job ads, mention cognitive and social skills more often in their job ads than employers hiring in a competitive labor market: we find that a 1% change in the local labor market HHI index is associated with an additional 0.10 ads mentioning social skills and 0.06 ads mentioning cognitive or organizational skills. This is equivalent to an increase of one-sixth of the overall mean. It is also approximately one-half the magnitude of increased skill demand associated with a 1% rise in the area's college graduate share, a major factor in the literature on skill-biased technical change (Moretti, 2004, 2011; Diamond, 2016). The relationship between market concentration and computer skills is also positive (0.02–0.06 additional ads, but similar in proportional terms). When we condition on firm-, occupation-, and city-level fixed effects, we still find large positive effects of labor market concentration on the demand for skills.

Labor market concentration is associated with larger upskilling in low-skilled occupations than in high-skilled ones. For low-skilled occupations (clerical, low-skill services, production, transportation), a 1% increase in the local labor market's HHI index results in 0.13 more ads asking for social skills and 0.09 more ads asking for cognitive skills. For high-skilled occupations (managerial and professional), the increases are only 0.08 and 0.04, and from a higher base. The difference in estimates between the two occupation types is large and statistically significant. In contrast, we find no difference by occupation group for other skill categories (organizational, computer). Furthermore, there is little evidence that this effect is due purely to differences in employer concentration across occupations. Instead, we find that employer market power is equally present in low- and in high-skilled professions, but its effect on upskilling is considerably stronger in low-skilled ones.

## 2 Literature review

This paper studies how employers' market power affects the demand for various skills in local labor markets. To the best of our knowledge, this is the first work that considers how a firm's competitive position in the inputs market affects its demand for different types of labor. We make three main contributions: first, we quantify the occurrence of upskilling across local labor markets that are more or less concentrated. Second, we identify the types of skills that drive this phenomenon: social, cognitive, and, to a lesser extent, organizational skills. Lastly, we show that, though labor market concentration is no more widespread at the low end than at high end of the skills distribution, upskilling occurs more in low-skill concentrated markets than in high-skill concentrated markets.

Our results inform the literature on the negative relationship between labor market concentration and the level of wages, and provide additional evidence in favor of employers' market power in hiring (Azar, Marinescu, and Steinbaum, 2017; Azar, Marinescu, Steinbaum, and Taska, 2018). We also interact with a literature investigating heterogeneity in the returns to skills by showing how an increase in employers' market power is associated with increased demand for cognitive and social skills (Deming, 2017; Deming and Kahn, 2018; Hershbein and Kahn, 2018). Finally, we contribute to a revived interest in secular trends in market power and the rising importance of large firms, by describing how labor market concentration affected skill demand in the last decade (Autor, Dorn, Katz, Patterson, and van Reenen, 2017; De Loecker and Eckhout, 2017; Eggertsson, Robbins, and Wold, 2018).

While our investigation of the demand for various skills is novel, labor market monopsonies are a well-studied topic in labor economics. As noted by Boal and Ransom (1997), the word "monopsony" was first used at the beginning of the 20th century by Joan Robinson, who conceived monopsony as analogous to monopoly (i.e. markets with a single buyer, or a single seller). In recent years, several studies have provided compelling empirical evidence of employer market power. 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. While these authors provide convincing evidence consistent with employer market power, these studies are not general enough to infer any conclusions about the macroeconomy. In this paper, on the other hand, we use comprehensive data on 108 distinct occupations in 382 metropolitan areas in order to accurately describe the relationship between labor market concentration and skill demand.

Recent work by Azar, Marinescu, and Steinbaum (2017) and Azar, Marinescu, Steinbaum, and Taska (2018) also favors an economy-wide approach, though the authors do not investigate changes in skill demand. Instead, they argue that employer market power is a pervasive phenomenon in U.S. labor markets and show that most U.S. local labor markets are highly concentrated according to the DOJ-FTC merger guidelines. Benmelech, Bergman, and Kim (2018), focusing on manufacturing, also provide evidence on wages that is consistent with employers’ monopsony power and conclude that “there is a negative relation between local-level employer concentration and wages, that is more pronounced at high levels of concentration and increases over time”.

The association of labor market concentration with lower wage levels seems robust. However, it is unclear whether this association is a result of decreased bargaining power for workers, reduced skill intensity and productivity, or a mixture of the two. This is not an idle distinction, as the macroeconomic consequences and the appropriate policy responses would vary substantially across these scenarios. If reduced competitive pressure induced employers towards a less skill-intensive input mix, the consequences of labor market concentration would indeed be manifested in lower wages, but no conclusion could be inferred about disproportionate bargaining power on the employers’ side. If, instead, increased market concentration is not associated with lower skill intensity, it is much more plausible to ascribe lower wages in concentrated markets to decreased workers’ bargaining power, with potentially far-reaching consequences for inequality. Our paper addresses presents robust empirical evidence in favor of increased demand for skills in concentrated markets. Therefore, we conclude that our evidence qualifies the negative relationship between labor market concentration and wage levels as indicative of significant concentration in U.S. local labor markets.

### 3 Data

Our data come from a unique source: microdata from approximately 160 million electronic job postings in the United States that span 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. Burning Glass Technologies (BGT) examines some 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 analytic products. With the breadth of this coverage, the resulting database purportedly captures a near-universe of jobs posted online.

The BGT data have both extensive breadth and detail. Unlike sources of vacancy data such

as `careerbuilder.com` or `monster.com`, which are based on a single job board, the data we use span multiple 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). 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 contain little information about the characteristics of vacancies. In contrast, the BGT data contain multiple standardized fields for each vacancy, notably including detailed information on occupation, geography, employer, and skill requirements. The last of these contains thousands of specific skills standardized from open text in each job posting. The data thus allow for a detailed analysis of skill requirements within and across occupations, firms, and labor market areas, enabling us to document the relationship between employers' market power and demand for various skills.

The data, however, are not perfect. Although roughly two-thirds of hiring is replacement hiring (Lazear and Spletzer 2012), vacancies in general will be somewhat skewed towards growing areas of the economy; indeed, Davis, Faberman, and Haltiwanger (2013) show that the distribution of vacancies in JOLTS over-represents growing firms. Additionally, our data cover only vacancies posted on the Internet. 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 other sources, and show that, although BGT postings are disproportionately concentrated in occupations and industries that typically require greater skill, the distributions are relatively stable across time, and the aggregate and industry trends in the quantity of vacancies track other sources closely.

Furthermore, not every job posting in the data contains a valid entry for every possible field. In many cases, these are “true” missings in that the text of the original posting made no mention of a given characteristic.<sup>2</sup> For example, some postings do not list an educational requirement or an explicit skill, while others, often posted by a third-party recruiter, do not mention an employer name. Given our research questions, we restrict our sample to ads that contain valid values for employer name, employer location, industry, and occupational code. This drops about 40 percent of postings—most on account of missing employer name. We also exclude firms that posted less than 5 ads per year or that are located outside metropolitan areas (as of 2013 delineations).<sup>3</sup>

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<sup>2</sup>BGT makes available the original text of the job postings it spiders, so we can confirm this pattern in a random subsample of the data.

<sup>3</sup>In work in progress, we are exploring the sensitivity of our results to bounding assumptions on posts

## 3.1 Skill taxonomy

In our analysis, we exploit five categories of skill requirements, utilizing the stated demand for skills that we classify as cognitive, social, and organizational, and stated demand for computer skills, either general or specialized.<sup>4</sup> These skill requirements represent a broad swath of human capital measures in which both employers and economists have interest. In addition, they reflect what the economics discipline has learned about technological change over the past 20 years (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,” 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); we define the post as having *specialized* computer skills if BGT specifies specialized software (e.g., AutoCAD, Python, inventory management software).

## 3.2 Urban labor markets

### 3.2.1 Market definition

We characterize a local labor market as an occupation-city pair in each year. Cities correspond to the 2013 Core-Based Statistical Areas with population over 50,000 (i.e. metropoli-

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lacking an employer name; the results are not sensitive to the minimum ad restriction.

<sup>4</sup>We plan to add education and experience requirements, as in Hershbein and Kahn (2018), in our next draft.

Table 1: 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++)

tan areas). As a result, there are 382 cities in our final dataset. 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 6-digit SOC classification, or even job title, 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—indeed, too fine an occupational classification would mechanically lead to a small number of firms posting jobs in each market, biasing upward our estimates of labor market concentration. On the other hand, too broad an occupational classification would erase important distinctions between heterogeneous skills used in different occupations. To assess how our results change with the level of detail in our definition of occupations, we will evaluate our results at the 2-digit SOC level (22 occupational groups) and 5-digit SOC level (449 broad occupations), as well.

As an example of the restriction we impose by assuming that markets are defined at the 4-digit SOC level, consider the four occupational groups: “Life Scientists” (1910), “Physical Scientists” (1920), “Social Scientists and Related Workers” (1930), and “Life, Physical and Social Science Technicians” (1940). These are part of the broader category “Life, Physical and Social Science Occupations” (19) and, because they have distinct 4-digit SOC codes, are considered different markets in our framework. “Life Scientists”, however, may be disaggregated into occupations such as “Agriculture and Food Scientists” (19-101), and “Biological Scientists” (19-102)<sup>5</sup>. In our framework, these are *not* considered different markets, as they share the same 4-digit occupational code.

We concentrate on urban labor markets for a few reasons: first, we avoid the natural correlation between rural-urban status and the level of labor market concentration. In rural counties, it is not unusual to have only a few employers in each labor market (or, in the case

<sup>5</sup>Furthermore, the broad occupation “Biological Scientists” can be divided in detailed occupations such as “Biochemists and Biophysicists” (19-1021), and “Microbiologists” (19-1022).

of so-called company towns, just one). Since the analysis of rural vs. urban labor markets is not the focus of this paper, we elect to study labor market concentration in urban settings, as we think this guarantees meaningful comparisons across markets. In addition, more than 80% of job-seekers apply to job openings in their same metro-area of residence (Marinescu and Rathelot, 2010). Thus, defining labor markets as the intersection of occupations and MSAs captures the clear majority of workers.

### 3.2.2 Descriptive analysis: concentration

Our final sample contains 17,543,471 employer-market-year cells, of which 15,032,577 have “active firms”, employers that post at least 5 job ads per year, regardless of market. For our empirical analysis, we concentrate on such active employers, but results are robust to relaxing this constraint. To properly identify employers’ names, we apply a series of cleaning and standardization routines so that, in the final sample, we have approximately 250,000 unique employers.<sup>6</sup> When we tabulate the density of the job-postings shares’ HHI, we find that the average labor market in the U.S. is moderately concentrated, with a mode between  $\log(\text{HHI})=5.9$  and  $\log(\text{HHI})=6.2$ , the equivalent of 27 and 20 (equal-sized) employers per market, and that the distribution is approximately lognormally distributed. There is, in addition, a significant right tail, as evidenced in figure 1, where  $\log(\text{HHI})\geq 8.1$  is equivalent to three or fewer employers.<sup>7</sup>

The average labor market in our data contains 216 job postings per year, and the average employer posts 134 job ads per year across all markets. Concentrated labor markets, however, tend to have fewer postings per year, and these postings tend to be for larger firms than in less concentrated markets, as seen in table 2. We compute the number of postings per firm in all markets (that is, in all locations and for all occupations), and then calculate the average per quartile of labor market concentration. The most concentrated markets are more likely to have posts from larger firms—those that post more ads across all markets. We interpret the number of postings per firm-year as a proxy for firm size.<sup>8</sup> Indeed, the relationship between

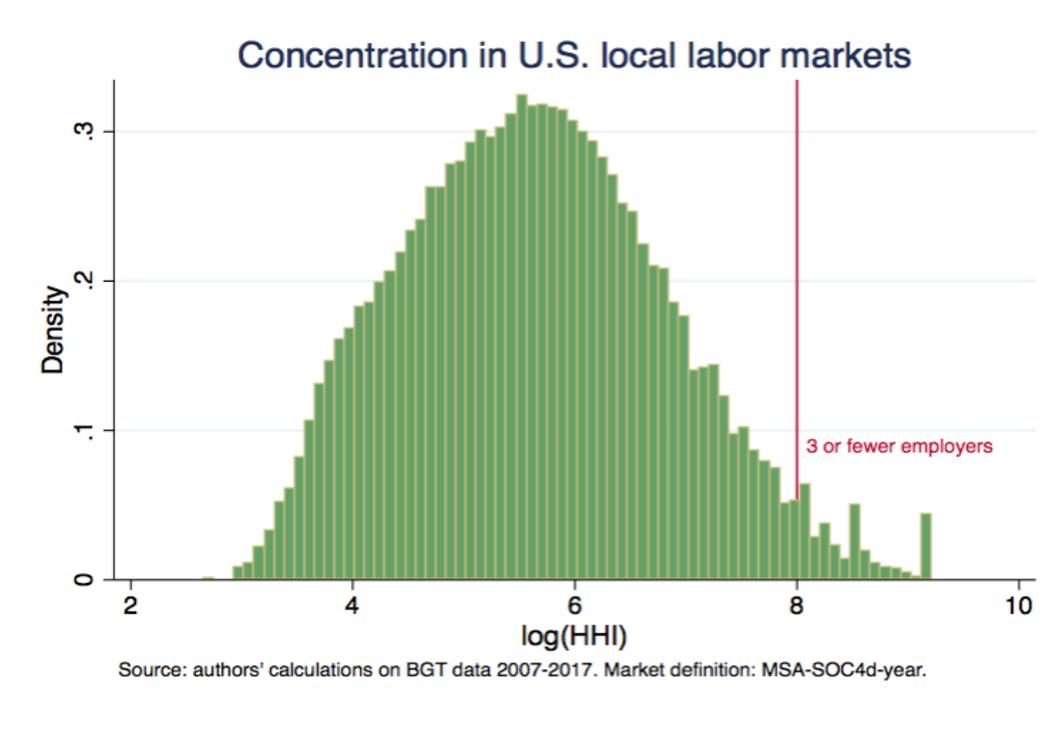
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<sup>6</sup>For example, we standardize employer names by dropping “Inc.”, “Incorporated”, “Corporation”, and other similar terms. We also correct common typos, such as “Incorporated” vs. “Incoprorated” and manually correct variant spellings for large employers, for example “Kohl’s” and “Kohls”.

<sup>7</sup>Note that all HHI calculations are made with unweighted firm-level vacancy shares. Appendix figure A.2 shows the HHI distribution in levels for both unweighted and employment-weighted markets; the right tail is even more pronounced in these figures. In regressions below we explicitly control for market size to account for the possible bias induced by weighting equally employers in small and large markets.

<sup>8</sup>In the appendix (figure A.3), we also show that employers in more concentrated markets exhibit less growth in their job posting volume between 2010 and 2017. We conclude that firms in more concentrated

Figure 1: Herfindahl-Hirschman index for U.S. local labor market: the average labor market is moderately concentrated (20-27 firms), with a significant right tail (3 or fewer firms).



firm-level job postings volume and labor market concentration is positive and monotonic (row 1 of table 2). 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 2). At the same time, markets above the 75th concentration percentile have on average 23 postings per year, while those below the 25th concentration percentile have on average 596 (row 3). These patterns together suggest that the most concentrated markets are dominated by a few large firms who have few postings in these markets, and that less concentrated markets have a greater number of smaller firms posting in them.<sup>9</sup>

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markets tend to have a larger volume of postings across all markets and grow at a slower pace over time, two facts consistent with these firms being larger.

<sup>9</sup>In work in progress, we compute similar concentration measures in the Longitudinal Business Database (LBD), a Census data product that contains information on employment for the universe of firms in the U.S. The LBD allows us to verify that the positive relationship between the level of labor market concentration

Table 2: Employer and market characteristics across different levels of labor market concentration. There is a positive relationship between the level of labor market concentration and firm-level volume of job postings.

Postings per ...	<i>Market's rank in concentration distribution</i>			
	Bottom quartile	Second quartile	Third quartile	Top quartile
firm-year	84	125	155	173
firm-MSA-year	5	5	5	5
market-year	596	171	77	23

### 3.2.3 Descriptive analysis: demand for skills

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 3). That said, social skills are the most frequently requested, while specialized computer skills the least.

## 4 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 log-HHI index of the market where the firm is active:

$$\# \text{ mentions skill } \mathbf{s}_{fmt} = \mu + \alpha_f + \alpha_{o(m)} + \alpha_t + \beta X_{c(m)} + \gamma \log(HHI)_{mt} + \varepsilon_{fmt} \quad (1)$$

where  $m$  denotes the market,  $o(m)$  the corresponding occupation (4-digit SOC codes),  $c(m)$

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and firm-level volume of job postings holds also in terms of firm-level employment and job creation.

Table 3: 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

the corresponding metropolitan area,  $t$  the year when the job was posted, and  $f$  the firm. In addition to fixed effects for firm, occupation, and year, we include a series of city-level controls  $X_{c(m)}$  to account for other determinants of local skill demand. Namely, we consider the size of the labor force (ages 18-65), the share of young people (ages 18-25), the share of college-educated workers (ages 23-65), and the local unemployment rate. All city-level variables except the local unemployment rate enter in 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 Current Population Survey. 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 4 and 5. In table 4 we concentrate on social and cognitive skills, 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 (1), with all city-level controls at year 2000. As explanatory variables are in log terms, we can interpret the coefficients as semi-elasticities—i.e.,  $dy/d \log x$  implies a 1% increase in the HHI index 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 3). 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 index 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 4 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 a metro area fixed effects alongside employer, occupation, and year fixed effects. These correspond to the following two specifications:

$$\# \text{ mentions skill } \mathbf{s}_{fmt} = \mu + \alpha_f + \alpha_{o(m)} + \alpha_t + \beta^{(1)} X_{c(m)}^{(1)} + \beta^{(2)} X_{mt}^{(2)} + \gamma \log(HHI)_{mt} + \varepsilon_{fmt} \quad (2)$$

$$\# \text{ mentions skill } \mathbf{s}_{fmt} = \mu + \alpha_f + \alpha_{o(m)} + \alpha_{c(m)} + \alpha_t + \gamma \log(HHI)_{mt} + \varepsilon_{fmt} \quad (3)$$

The coefficient on the concentration measure ( $\gamma$ ) barely changes in these different specifications. We choose equation (3) a model with employer-, city-, occupation-, and year-fixed effects as our preferred specification going forward, and proceed to investigate how labor market concentration affects the demand for different types of skills. Figure 2 shows the equivalent of regression (3) 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 and well-approximated by a linear regression.

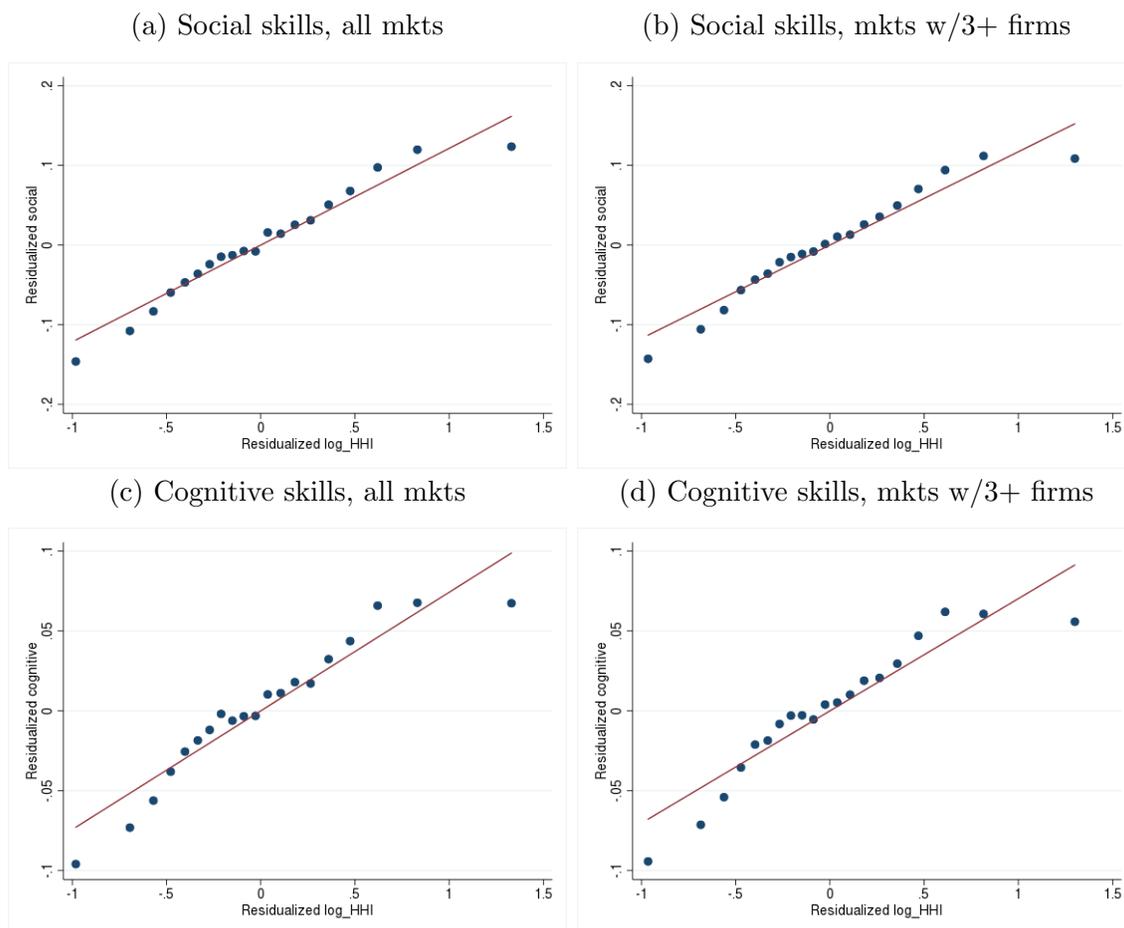
The effect of labor market concentration on the demand for skills is heterogeneous across skill categories. A 1% increase in the HHI index raises the demand for cognitive skills roughly four times as much as the demand for specialized computer skills, as illustrated in table 5. Specifically, a 1% increase in the local labor market HHI is on average associated with 0.12 more ads stating demand for social skills, 0.07 for cognitive skills, 0.08 for organizational skills, 0.05 for general computer skills and 0.02 for specialized computer skills. As shown by figure 2, these results are also robust to the exclusion of high-concentration markets—i.e., markets whose HHI is at least 5000 (duopsony and monopsony markets).

Table 4: 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		
	<b>0.101</b> (28.74)	<b>0.104</b> (34.65)	<b>0.117</b> (40.78)	<b>0.064</b> 18.97	<b>0.064</b> 21.37	<b>0.070</b> 26.47
<b>log(HHI)</b>						
log(labor force)	0.245 (60.32)	0.216 (38.65)	–	0.183 (50.30)	0.141 (28.91)	–
log(college share)	0.206 (24.61)	0.168 (21.51)	–	0.179 (20.22)	0.142 (19.17)	–
log(unempl. rate)	0.008 (1.30)	-0.040 (-6.73)	–	0.015 (2.60)	-0.031 (-5.76)	–
mkt size	–	0.0001 (8.49)	0.0001 (8.46)	–	0.0001 (8.72)	0.0001 (8.72)
Employer FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	X	X	✓	X	X	✓
<i>N</i>	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

Figure 2: The positive relationship between labor market concentration and skill demand.



## 5 Labor market concentration for low- and high-skill jobs

We have established two novel facts so far: (i) labor market concentration is associated with an increased demand for skills, even within narrow occupational groups or within job postings by the same employer in different markets; and, (ii) the increase in skill demand is disproportionately concentrated in the categories of social, cognitive, and organizational skill, with much smaller effects for computer-related skills.

In this section, we proceed to analyze the heterogeneous effects of labor market concentration for high- and low-skilled occupations. First, we show that the data do not support the

Table 5: Effect of concentration on demand for various skills: a 1% increase in the HHI index 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 (40.78)	0.115 (38.65)	0.070 (26.47)	0.068 (24.60)	0.077 (36.82)	0.076 (35.19)
	Computer, general		Computer, specific		Any computer	
log(HHI)	0.049 (31.97)	0.048 (30.30)	0.018 (4.34)	0.017 (4.05)	0.060 (15.32)	0.059 (14.35)
Employer FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
MSA FE	✓	✓	✓	✓	✓	✓
Excludes HHI $\geq$ 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 from a separate regression.

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 larger for low-skilled occupations.

## 5.1 Are high-skill labor markets more concentrated than low-skill ones?

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.<sup>10</sup> When we correlate these binary skill indicators between 108 4-digit SOCs

<sup>10</sup>The first group includes management; business and financial; computer and math; architecture and engineering; life, physical, and social sciences; community and social services; legal; education; arts, sports, and media; healthcare; and healthcare support occupations. The latter includes protective services; food

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.

## 5.2 Upskilling and concentration in high- and low-skilled labor markets

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 (3) 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 6 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 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 vs. 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 log-HHI coefficients for low- and high-skill occupations, while positive, is not statistically significant for computer and organizational skills.

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preparation and serving; cleaning and maintenance; personal services; sales; office and administrative; farming, fishing, and forestry; construction and extraction; installation, maintenance, and repair; production; and transportation occupations.

Table 6: Effect of concentration on the demand for various skills: heterogeneity across occupations (low- vs. high-skilled).

	Social	Cognitive	Organizational
high-skill	0.081 (19.36)	0.045 (11.10)	0.061 (24.84)
low-skill	0.131 (36.99)	0.093 (27.10)	0.064 (28.65)
	Computer, general	Computer, specific	Any computer
high-skill	0.375 (22.25)	0.010 (1.79)	0.044 (8.46)
low-skill	0.0397 (20.20)	0.026 (5.70)	0.057 (12.39)
Employer FE	✓	✓	✓
Occupation FE	✓	✓	✓
Year FE	✓	✓	✓
MSA-level controls	✓	✓	✓
<i>N</i>	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

## 6 Conclusions

This paper investigates how labor market concentration is related to the demand for various skills in a local area. Following the previous literature, we identify five skill dimensions: social, cognitive, organizational, specific and general computer skills. We then use novel, comprehensive data on the near-universe of job postings across U.S. metropolitan areas, and show that employers searching for workers in more concentrated labor markets demand higher skills, especially along the cognitive, social, and organizational. In our preferred specifications, using a rich set of fixed effects for employer, occupation, city, and year, we find that a 1% increase in labor market concentration is associated with an additional 0.12 ads asking for social skills, 0.07 ads asking for cognitive skills, 0.08 ads asking for organizational skills, and 0.06 ads asking for computer skills. Though these numbers may seem small in absolute value, they represent between 10% and 18% of the respective means, and are

equivalent to one-half the magnitude of increased skill demand associated with a 1% rise in the area's college graduate share. Our findings remain unchanged after the exclusion of markets with one or two advertising employers, or controlling for city size and the local share of college-educated workforce.

The positive effect of labor market concentration on skill requirements is larger for low-skilled than for high-skilled occupations. For low-skilled occupations (clerical, personal services, production, transportation), a 1% increase in the local labor market HHI results in 0.13 more ads asking for social skills and 0.09 more ads asking for cognitive skills. For high-skilled occupations (managerial and professional), the increases are only 0.08 and 0.04, and from a higher base. The difference in estimates between the two occupation types is large and statistically significant. In contrast, we find no difference by occupation group for other skill categories (organizational, computer). Furthermore, there is little evidence that this effect is due purely to differences in employer concentration across occupations. Instead, we find that employer market power is equally present in low- and in high-skilled professions, but its effect on upskilling is considerably stronger in low-skilled ones.

These results underscore a potential reason for concern. Recent literature has argued for an increasing trend in labor market concentration and output market concentration in recent decades (Benmelech, Bergman, and Kim, 2018; de Loecker and Eeckhout, 2017), and evidence is mounting for its negative correlation with wages (Azar, Marinescu, and Steinbaum, 2017). In this paper, we present evidence of sustained upskilling within narrow occupational groups, and even within positions at the same firm, for employers hiring in concentrated labor markets, confirming the interpretation of the data in terms of wide-spread employer market power. We also show that upskilling is more prevalent among low-skill concentrated markets than high-skill ones, suggesting that employer market power has a larger effect on the career of low-skill workers than on that of high-skill workers. As these workers are also more vulnerable to employment instability and low wage growth, an increase in labor market concentration may further strain unskilled workers' welfare and success in the labor market.

In future work, we plan to pursue three steps. First, we will investigate other measures of employer market power, including (i) the share of job postings accruing to the top 4 (10) firms in each market, from the BGT data, and (ii) employment-based HHI measures, from the Longitudinal Business Database (LBD). Leveraging the richness of Census and BGT data, we will be able to compute firm-level employment- and vacancy-shares, so to calculate and compare the cross-sectional variation and time trend of different measures of labor market concentration. Second, we plan to relate our measures of market power in

hiring to the level of posted and realized wages in each market and skill category, using a combination of proprietary data from BGT and publicly-available data from Occupational Employment Statistics. This exercise will complement existing literature and we expect it will confirm our interpretation of the data as supporting the presence of employers' market power. Third, we will relate our input markets measures of concentration to measures based on output markets—i.e., the HHI of sales and the share of sales accruing to the top 4 (10) firms in each market—and study (i) how input market concentration relates to output market concentration in the cross-section and over time, and (ii) how concentration in either the labor or the product market affects firm-level demand for various skills.

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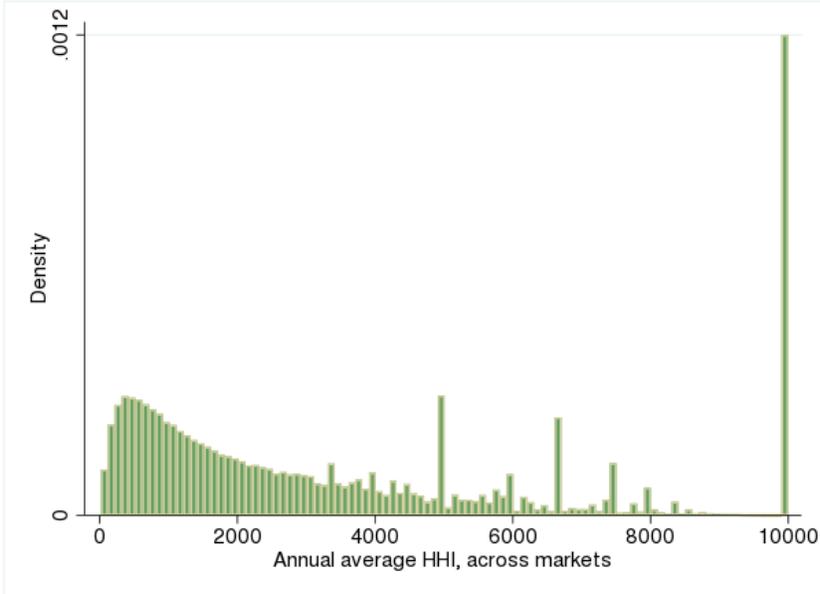
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# Appendix

Figure A.1: Distribution of HHI across markets and across postings (cf. figure 1 in text).

(a) The average market is moderately concentrated, but there is significant mass in the right tail.



(b) The average posting is in a fairly unconcentrated market.

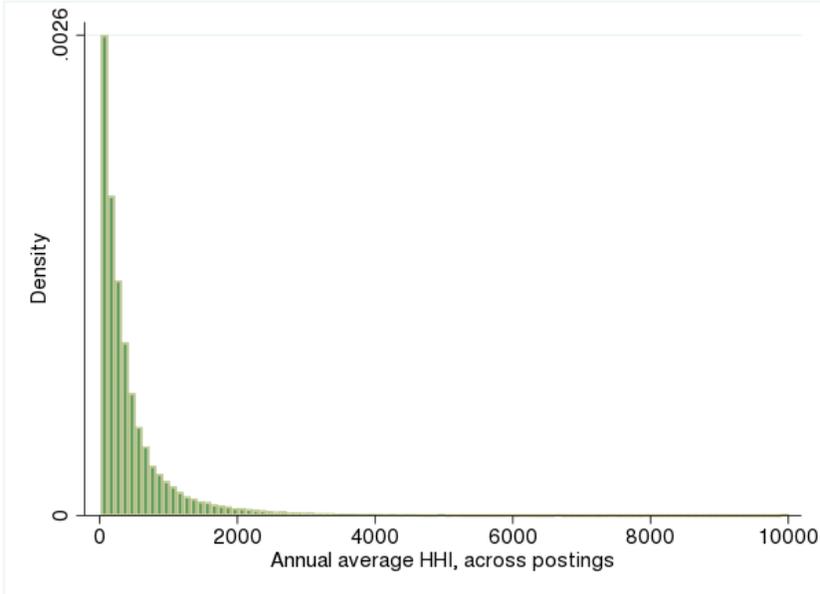
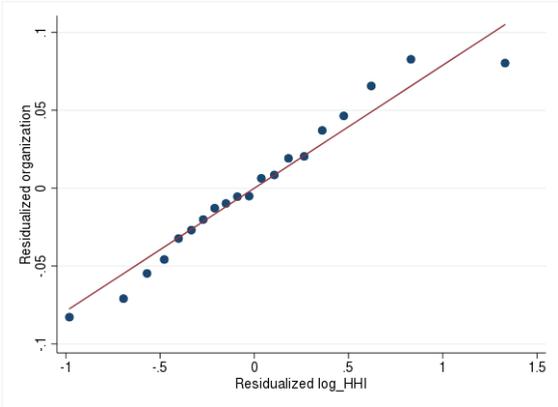
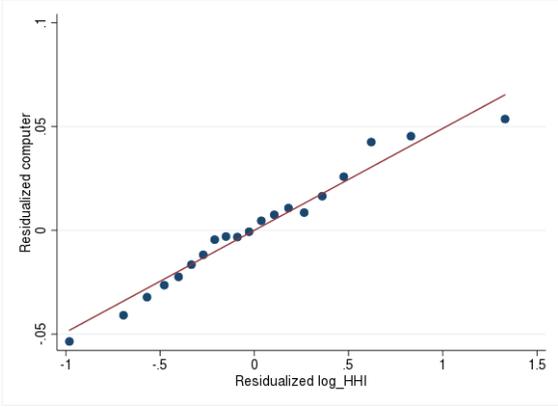


Figure A.2: The positive relationship between labor market concentration and skill demand, additional skill dimensions (cfr. figure 2 in text).

(a) Organizational skills, all mkts



(b) Computer general skills, all mkts



(c) Computer specific skills, all mkts

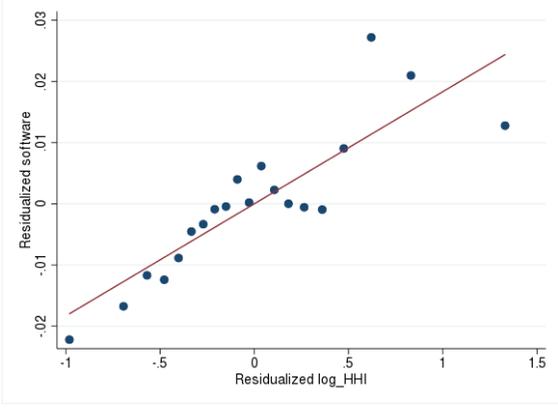


Figure A.3: Labor market concentration is computed in 2007, while growth in firm-level job postings is computed over the years 2010–2017. Firms that posted jobs in more concentrated markets in 2007 saw more variation in posted job growth between 2010–2017 than firms who posted in less concentrated markets in 2007 (bottom vs. top panel). Firms posting in initially more concentrated labor markets are more likely to see a reduction in job postings than firms posting in initially less concentrated labor markets.

