

# Monopsony and Concentration in the Labor Market: Evidence from Vacancy and Employment Data\*

**Brad Hershbein**  
W.E. Upjohn Institute

**Claudia Macaluso**  
UIUC

**Chen Yeh**  
UIUC

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## Abstract

This paper characterizes the cross-sectional incidence, time dynamics and economic significance of employer market power in the U.S. labor market. We do so in two ways: first, we estimate plant-level markdowns using administrative data for U.S. manufactures and, second, we calculate market-level concentration indexes for the universe of U.S. employers. We quantify markdowns — the wedge between a plant’s marginal revenue product of labor and its wage — building on state-of-the-art industrial organization estimation techniques. We find that markdowns average at 78 percent in U.S. manufacturing and there is a substantial amount of dispersion across firms, even within detailed industries. We then document that markdowns are positively correlated with size — implying that measures of concentration based on firms’ employment shares are informative on labor market power. Given this positive relationship, we construct concentration indexes for the universe of U.S. employment and online vacancies. We find that (i) less than 5 percent of new jobs in the last decade are in concentrated markets, (ii) local labor market concentration has decreased while national labor market concentration has increased since the early 1980s. To understand this diverging trend, we use an Olley-Pakes statistical decomposition that identifies what can drive a wedge between local and national concentration. Estimating this decomposition, we find that a sustained decrease in the spatial dispersion of U.S. employment is able to account for the divergence. We interpret this evidence as suggesting that, over the last decades, U.S. local labor markets have become more and more “alike” in terms of their industry and employment composition. Finally, we provide evidence that local labor market concentration is negatively correlated with wages but positively correlated with skill demand — a phenomenon we refer to as “upskilling”. Our findings imply that policy interventions in oligopsonistic labor markets are unlikely to be successful if predicated on industry-level indicators or implemented with increases in the federal minimum wage.

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\*Contact: Hershbein ([hershbein@upjohn.org](mailto:hershbein@upjohn.org)), Macaluso ([cmacaluso.econ@gmail.com](mailto:cmacaluso.econ@gmail.com)) and Yeh ([chen.yeh@gmail.com](mailto:chen.yeh@gmail.com)). We thank Adrien Auclert, Christian Bayer, Steven J. Davis, Jan Eeckhout, Jason Faberman, Lisa Kahn, Loukas Karabarbounis, Ayşegül Şahin, and the audiences at the Barcelona Summer Forum EGF group, FRB Richmond Conference “Market Structure and the Macroeconomy”, ASSA/AEA Meetings 2019, IZA Workshop: Matching Workers and Jobs Online, Bonn 2018 EM3C conference, *brq* Workshop “Firms, Jobs, and Inequality”, University of Oslo-CEPR “Micro-consistent Macro” conference, Federal Reserve Board of Governors, FRB of Richmond, FRB of Chicago, and University of Connecticut for insightful comments. Andrea Atencio provided excellent research assistance. This research was conducted while Claudia Macaluso and Chen Yeh were Special Sworn Status researchers at the Federal Statistical Research Data Center in Chicago, IL. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. First version: May 15, 2018.

# 1 Introduction

The extent and variation of employers' market power potentially affects several recent macroeconomic trends of concern, such as the decline in labor market fluidity, sluggish wage growth, and increasing inequality. 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. Hence, quantifying employers' market power and understanding how these effects take place is fundamental to devise appropriate policy responses. The presence of employer market power is particularly relevant when evaluating labor market policies that directly affect workers' compensation and mobility, such as changes in the minimum wage, or assessing regulations aimed at limiting the growth of large firms. These and other policies contrasting a perceived increase in employers' market power have recently been actively considered by policy makers (cfr. FTC, October 15-17 2018). Though direct measures of employer market power would be valuable to inform the policy debate, they are not yet available.

Indirect measures of employer market power based on concentration are, on the other hand, commonly used in both academic literature and policy practice. However, concentration measures are quite sensitive to the chosen definition of a labor market (especially its geographic boundaries). While this sensitivity has been documented, there is no consensus on the interpretation of the differences that arise from it. Furthermore, it is unclear from a theoretical standpoint whether a market's extent of competition and its level of concentration are positively correlated (Syverson, 2019).

Our paper addresses precisely these two gaps: first, we provide a direct measure of employer market power by estimating plant-level markdowns. Second, we reconcile the different measures of labor market concentration discussed in the literature and provide an interpretation for their differences. In particular, we compare direct measures, such as markdowns, to concentration indexes based on employment shares and find a positive relationship between the two. In addition, we propose a statistical decomposition à la Olley and Pakes (1996) to reconcile and interpret the divergence between indexes of concentration at the local and national level. We then show the cross-sectional and time-series properties of these different measures of employer market power, therefore providing a thorough characterization of its cross-sectional incidence, time dynamics and economic significance in the U.S. labor market.

We start by estimating and characterizing the distribution of plant-level markdowns. Markdowns reflect an employer's ability to compensate its workers below their marginal revenue product. In our baseline measure, we assume that firms take monopsony forces into account by internalizing a finitely elastic labor supply curve. We then show that, in a general setting, plant-level markdowns are equal to the ratio of (i) the output elasticities with respect to labor and (ii) the product between plant-level markups and revenue labor shares. To empirically implement this insight, based on Hall (1988), we use administrative data for the U.S. manufacturing sector and closely follow the production function estimation approach in De Loecker and Warzynski (2012) and Akerberg, Caves and Frazer (2015). We find that markdowns are sizable, as they average at 78 percent, but are still in the lower bound of estimates implied by the current literature (cfr.

Manning (2003), Webber (2015)). Furthermore, there is a substantial amount of dispersion. In particular, we find a high degree of variation in markdowns even within detailed industries (3-digits NAICS): the average within-industry interquartile range is 64 percent.

A significant conceptual challenge in the study of monopsony using concentration stems from the fact that different theoretical frameworks imply either a positive or a negative relationship between a market's extent of *competition* and its level of *concentration* (Syverson, 2019). In this paper, we derive an explicit and testable condition for indexes 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 a firm's share of local employment. Intuitively, this implies that firms with a larger share of local employment are able to drive a larger wedge between their marginal product of labor and the wage they pay to their workers. Using our markdown estimates for U.S. manufactures, we test the relationship between firm-level markdowns and local shares of employment and find a positive association. We interpret this evidence as confirming that concentration indexes are informative on monopsony power.

Given the empirical evidence on the positive relationship between markdowns and concentration, we construct concentration indexes for the universe of U.S. employment and online vacancies. 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 percent of new U.S. jobs are in moderately concentrated local markets; (ii) local labor market concentration decreased over time, dropping by at least 25 percent since 1976. Similar to the findings by Rossi-Hansberg, Sarte and Trachter (2018) and Rinz (2018) however, we also document that national employment concentration has been increasing since the early 1980s.

How to interpret the divergence between local and national labor market concentration? We propose a statistical decomposition in the spirit of Olley and Pakes (1996) and show that this decomposition rationalizes the observed wedge between local and national concentration over time by (i) a declining covariance between the size of a local labor market and its concentration, and/or (ii) a decrease in the spatial dispersion of employment. We find that the latter predominates in the data, implying that U.S. local labor markets have become more and more "alike" in terms of their industry and employment composition. In other words, the U.S. economy is converging towards a scenario in which employment is evenly spaced across local labor markets.

In the remainder of the paper, we establish the cross-sectional properties of local labor market concentration. First, we confirm the negative correlation between local labor market concentration and wages — first documented in Azar, Marinescu and Steinbaum (2017) and expanded in Benmelech, Bergman and Kim (2018) for the manufacturing sector. However, we find a smaller elasticity of wages to concentration than previous studies. Furthermore, our individual-level analysis shows that the negative correlation between concentration and wages is entirely accounted for by college-educated workers.

When labor is heterogeneous, monopsony potentially affects both the quantity and the quality of labor. In fact, we document that monopsony power does not manifest itself only through a negative correlation with wages, but also through a positive effect on the demand for skills (“upskilling”). We show that upskilling in concentrated markets is quantitatively important by correlating the skill content of new jobs (vacancies) to the level of local labor market concentration. Following the skill categorization in Deming and Kahn (2018), and Hershbein and Kahn (2018), we show that the effect of labor market concentration on the demand for skills is positive and particularly strong for social and cognitive skills: a 1 percent 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 these skills, these numbers are large as they represent 10 percent and 13 percent 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 positive association between concentration and the demand for skills. We argue that the upskilling effects we document constitute a policy challenge that is not readily addressed by traditional instruments such as increases in the minimum wage.

**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 (De Loecker and Eeckhout, 2017) and industry-level concentration of sales (Autor et al., 2017), and suggested that the latter could be a unifying explanation behind many of the observed secular trends (De Loecker and Eeckhout, 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 primarily 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 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; Ashenfelter, Farber and Ransom, 2011). 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 employers and online vacancies 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. Berger, Herkenhoff and Mongey (2018) quantify the welfare cost of labor market power using an oligopsony version of the framework by Atkeson and Burstein (2008). The authors use heterogeneous responses across firms to changes in state-level corporate taxes to identify the key parameters of their structural model. Their model implies that markdowns are increasing in firm size; a prediction that is consistent with our empirical results. In a recent paper, Rinz (2018) studies employment concentration in all industries and documents a negative time trend consistent with our findings. On the other hand, Autor et al. (2017) find an *increasing* trend in the national concentration of employment using Census data for selected industries. In this paper, we show that the decline in local labor market concentration is robust across various datasets and measures, including occupation-level vacancy flows, and we interpret its divergence over time from national concentration by exploiting a statistical decomposition in the spirit of Olley and Pakes (1996).

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.** The paper is organized as follows. In section 2 we illustrate how we measure and estimate markdowns, and discuss their cross-sectional distribution and time-series evolution. In section 3 we introduce our preferred concentration measures and discuss the strengths and pitfalls of our empirical strategy. We document concentration trends in various measures of labor utilization and discuss how to reconcile the diverging patterns between local and national concentration trends. Section 4 provides conditions that are required for the HHI of employment to be a good proxy of monopsony power and verifies them in the data. Section 5 proceeds with our wage compression and upskilling results. Finally, section 6 takes stock of all our empirical findings and concludes.

## 2 Measures of employer market power: markdowns

We start our analysis of monopsony in the U.S. labor market by estimating a direct measure of employer market power: markdowns. The goal is to provide a measure of employer’s market power that is rooted in basic economic principles, i.e. firms’ profit maximization, and provides direct evidence on the extent of monopsony in the U.S. labor market. In this section, we first set out our basic framework and show the relationship between the elasticity of the labor supply at the firm-level and markdowns. Then, we use the firm’s dual problem (cost minimization) to set out an estimation strategy modeled on De Loecker and Warzynski (2012). Using this strategy, we retrieve plant-level markdowns in the U.S. manufacturing sector in an environment that also allows for positive markups. We conclude by discussing the distribution of markdowns and the implications of our findings.

### 2.1 A stylized framework with markdowns

Consider how an individual employer’s monopsony power is captured by its ability to compensate its workers below its marginal revenue product of labor. We refer to this gap, expressed in percentage terms, as a firm’s “markdown”. Note that a firm’s markdown is negatively correlated with its perceived labor supply elasticity. To see this, consider a firm’s profit maximization problem:

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

where we dropped the firm’s index without loss of generality. Then, a firm’s optimality condition can be rearranged as:

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

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:

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

In the following section we argue that, although estimating a firm’s perceived elasticity of labor supply in a general setting is extremely challenging, one can use insight from Industrial Organization literature to

estimate markdowns. Once markdowns are estimated, one can use the above structural relationship to test the cross-sectional properties of the labor supply elasticities — specifically how they vary by industry and with a firm’s size.

Finally, we define employers’ market power at the labor market level as an employment-weighted average of individual firms’ monopsony power:

$$\mathcal{M}_{j\ell} = \sum_{f \in F(j,\ell)} \omega_f \mu_f \quad (2)$$

where  $\mu_f$  is a firm  $f$ ’s markdown and  $\omega_f$  denotes its employment share in labor market  $(j, \ell)$ .

## 2.2 Estimating markdowns

In this section we propose a methodology to retrieve markdowns for U.S. manufactures by exploiting the insights of Hall (1988) and De Loecker and Warzynski (2012). The key observation is that the wedge between (a) a firm’s markup and (b) the ratio of its output elasticity and revenue share for labor is informative for a firm’s markdown. In fact, we argue that this wedge exactly represents a firm’s markdown in the absence of adjustment costs and is, in general, an upper bound.

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

$$\min_{N \geq 0} w(N) \cdot N \quad \text{s.t.} \quad F(N) \geq Y \quad (3)$$

where  $F(N)$  denotes a firm’s production function. Denoting the associated Lagrangian multiplier by  $\lambda$ , a firm’s optimality condition can be written as:

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

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

$$\frac{\varepsilon_S + 1}{\varepsilon_S} = \nu^{-1} \cdot \frac{F'(N)N}{F(N)} \cdot \alpha_N^{-1} \quad (4)$$

$$\mu \equiv \nu^{-1} \cdot \theta_N \cdot \alpha_N^{-1} \quad (5)$$

where  $\alpha_N$  denotes a firm’s revenue share of labor and  $\theta_N$  the elasticity of output with respect to labor. Furthermore,  $\nu$  is a firm’s price-cost markup, i.e. the wedge between its price and marginal cost of production. Therefore, we can construct (upper bounds for) markdowns  $\mu$  if we have estimates for three objects: a firm’s markup  $\nu$ , its output elasticity for labor  $\theta_N$  and its revenue share of labor  $\alpha_N$ . We will retrieve these

parameters using comprehensive administrative data on U.S. manufacturing plants (see section 2.3). Specifically, note that  $\alpha_N$  is directly observable, whereas markups  $\nu$  and output elasticities  $\theta_N$  must be estimated. We do this in manufacturing markets using the methodology from De Loecker and Warzynski (2012) and Akerberg, Caves and Frazer (2015).

Note that our approach allows us to explicitly distinguish between market power in output and labor markets. To do so however, we are required to obtain a measure for price-cost markups. While we leave the details of the estimation for the appendix, it is important to underline how we identify these markups  $\nu$ . Whenever an input is assumed to be flexible, i.e. it is not subject to monopsony forces or adjustment costs, Hall (1988) showed that the gap between a flexible input’s output elasticity and its revenue share is equivalent to a firm’s markup.

Pinpointing a flexible input is difficult in most data sets (e.g., Compustat) since most inputs are not registered separately but are rather classified into groups following accounting standards. However, expenditures on capital, labor, material and energy inputs are available separately in the ASM and CM. While some of the discussion on measuring market power has revolved on what constitutes a flexible input (e.g., Traina, 2018), we follow the convention in the Industrial Organization literature instead by assuming that material inputs are flexible (see De Loecker and Warzynski, 2012). Given our expression in (5), this means that estimating markdowns boils down to obtaining output elasticities through production function estimation techniques.

The advantage of our “production function” approach is that we do not need to make any assumptions on the sources of market power in order to quantify markdowns. In particular, we do not need to take a particular stance on the market structure for labor and the functional form of labor supply curves that firms are facing — a distinguishing feature of this paper with respect to fully-developed structural estimation efforts as in, for example, Berger, Herkenhoff and Mongey (2018). Furthermore, we do not need to make any assumptions regarding the flexibility of other inputs (including labor) besides material inputs. Our approach is valid as long as firms are subject to some finitely elastic labor supply curve and material inputs are flexible.

We regard the generality of our approach as one of this paper’s major attractive points. However, the implementation of our approach obviously does require some assumptions. Specifically, we are required to make assumptions on a firm’s production technology. To remain flexible though, we assume that gross output follows a translog specification. This comes at several advantages. First, the translog specification can be interpreted as a second-order approximation to *any* arbitrary production function (see De Loecker and Warzynski, 2012). Hence, it is much more general than a Cobb-Douglas specification. Second, output elasticities are allowed to vary across plants within a given industry under the translog specification. Thus, variation in markdowns is not solely inferred from the variation in input shares. Finally, we impose that the parameters of the production function vary across detailed industry groups but are constant over time. However, this is without much loss of generality.<sup>1</sup>

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<sup>1</sup>Under a translog specification, this does *not* imply that output elasticities are constant over time. This is because output



To estimate the parameters for each industry’s translog production function, we impose the standard assumptions associated with the “proxy variable” method for materials as mentioned in Levinsohn and Petrin (2003) and De Loecker and Warzynski (2012). While these assumptions may appear restrictive at first sight, all of the required restrictions nest standard assumptions in canonical models of firm dynamics.<sup>2</sup>

A potential point of concern however lies in whether the imposed “proxy structure” achieves point identification. In particular, Gandhi, Navarro and Rivers (forthcoming) show that the assumptions of the proxy variable method are insufficient to point identify production function parameters and additional sources of variation in the demand for flexible inputs are required. Recently however, Flynn, Gandhi and Traina (2019) have argued that this criticism can be circumvented if the returns to scale of the production function is known. They suggest that constant returns to scale is an useful benchmark and this additional assumption performs “remarkably well” in their Monte Carlo simulations.<sup>3</sup>

### **2.3 Data: the CM and ASM**

For the estimation of markdowns, we use two administrative datasets from the Census Bureau: the Census of Manufactures (CM) and the Annual Survey of Manufactures (ASM). The Census of Manufacturing is a quinquennial survey (carried out in years ending at “2” and “7”) that covers the universe of manufacturing establishments. The main advantage of using the CM is that numbers for revenues and inputs are available at the establishment level which are necessary ingredients for production function estimation. Measures for output (or deflated revenues) and inputs, such as capital, labor, material and energy inputs, are constructed with the use of deflators from the NBER-CES Manufacturing Database and follow standard procedures that are described extensively in, for example, Syverson (2004a) and Kehrig (2015).

In order to construct markdowns for non-Census years, we use the Annual Survey of Manufactures (ASM) which contains a representative sample of manufacturing plants. This sample rotates in years ending in “4” and “9”. While large plants are sampled with probability near unity, small plants (in terms of revenues and/or employment) are less frequently sampled in the ASM. However, the Census Bureau does provide sampling weights to keep the sample representative for the manufacturing sector. Our main results in the following subsections are based on a non-balanced panel for manufacturing plants in years 1976 – 2014. To avoid artificial spikes in Census years, note that we only keep those plants in Census years that are in the rotating sample of the ASM for that particular year unless noted otherwise.

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elasticities are allowed to vary with the level of a firm’s inputs which display time variation. As mentioned in the above, this assumption is fairly harmless since our results can be extended to allow for time-varying production parameters as well.

<sup>2</sup>In particular, our approach explicitly nests Cobb-Douglas technologies with productivity processes that display significant persistence, e.g. AR(1) process.

<sup>3</sup>While we have not imposed constant returns to scale in our current estimation procedure, our results indicate that we are not far off this benchmark. This seems consistent with recent work by Syverson (2004a) and Foster, Haltiwanger and Syverson (2008) who also look at samples consisting of manufacturing plants only. In a future draft, we will show the robustness of our estimates when the assumption of constant returns to scale has been implemented.

## 2.4 Markdowns in U.S. manufacturing

### 2.4.1 Cross-sectional distribution

Table I: Summary statistics on markdown distributions by manufacturing industry group.<sup>a</sup>

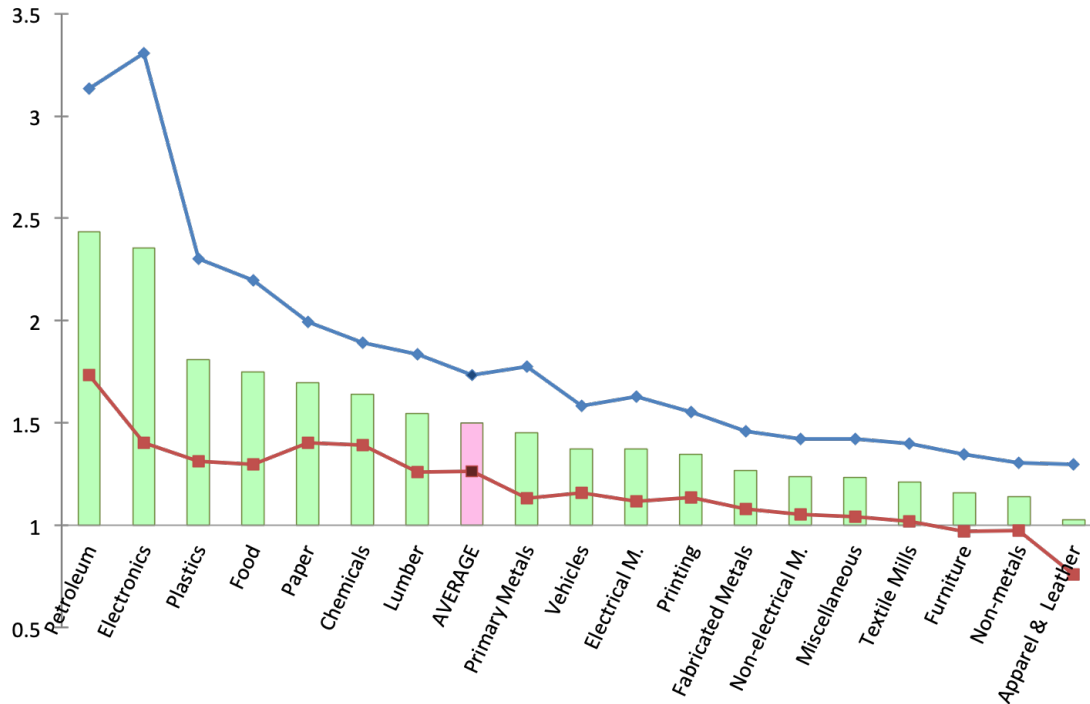
| INDUSTRY GROUP              | Mean                    | Median | IQR   |
|-----------------------------|-------------------------|--------|-------|
| Food and Kindred Products   | 2.012                   | 1.747  | 0.902 |
| Textile Mill Products       | 1.537                   | 1.210  | 0.416 |
| Apparel and Leather         | 1.666                   | 1.028  | 0.426 |
| Lumber                      | 1.930                   | 1.547  | 0.501 |
| Furniture and Fixtures      | 1.358                   | 1.157  | 0.333 |
| Paper and Allied Products   | 1.862                   | 1.697  | 0.577 |
| Printing and Publishing     | 1.826                   | 1.345  | 0.470 |
| Chemicals                   | 2.077                   | 1.640  | 0.989 |
| Petroleum Refining          | 2.708                   | 2.434  | 1.906 |
| Plastics and Rubber         | 1.972                   | 1.808  | 0.591 |
| Non-metallic Minerals       | 1.396                   | 1.140  | 0.375 |
| Primary Metals              | 1.579                   | 1.452  | 0.511 |
| Fabricated Metal Products   | 1.517                   | 1.268  | 0.368 |
| Non-electrical Machinery    | 1.308                   | 1.236  | 0.538 |
| Electrical Machinery        | 1.457                   | 1.371  | 0.381 |
| Motor Vehicles              | 1.524                   | 1.371  | 0.381 |
| Computer and Electronics    | 3.032                   | 2.355  | 1.399 |
| Miscellaneous Manufacturing | 1.422                   | 1.232  | 0.381 |
| AVERAGE                     | 1.788                   | 1.499  | 0.644 |
| ESTIMATION SAMPLE           | 1.449 · 10 <sup>6</sup> |        |       |

<sup>a</sup>Data: Annual Survey of Manufactures 1976–2014. Markdowns estimated under the assumption of a translog specification for gross output. Each industry group in manufacturing corresponds to the manufacturing categorization of the BEA which approximately follows a 3-digit NAICS specification.

Table I and figure 1 illustrate the distribution of estimated plant-level markdowns in U.S. manufacturing. The data suggests that the average plant operates in a monopsonistic environment. Markdowns are sizable and considerably larger than 1. Averaging across industries, we find that the median plant features a markdown of 1.499 (or 49.9%), with the minimum value equal to 1.028 (or 2.8%) in Apparel and Leather and the maximum value equal to 2.434 (or 243.3%) in Petroleum Refining. Despite the fact that estimated markdowns are significantly larger than 1, it is worth noting that these levels are lower than what implied by previous estimates of the labor supply elasticity (see Manning, 2003).

We furthermore document a substantial amount of heterogeneity in plant-level markdowns, both across and within industries. The average within-industry interquartile range of markdowns is 1.64 or 64%, larger than the median. Though different industries display different average markdowns, most of the variation in markdowns originates across plants *within* the same industry. This fact suggests that heterogeneity in

Figure 1: The distribution of markdowns across U.S. manufacturing plants, by detailed industry ( $x$ -axis). The green bars depict the median while the distance between the blue and the red line is equal to the interquartile range. The average markdown is 1.78 (78%), with substantial heterogeneity both across and within industries. Source: authors' calculations from ASM/CM data in 1976–2014.



markdowns is likely related to idiosyncratic factors, such as plant-level productivity differences or specific human capital, rather than industry-wide characteristics, such as legacy structure, institutional agreements or industry regulations (cfr. dispersion in revenue TFPR in narrowly defined manufacturing industries as documented by Syverson, 2004b).

## 2.4.2 Trends

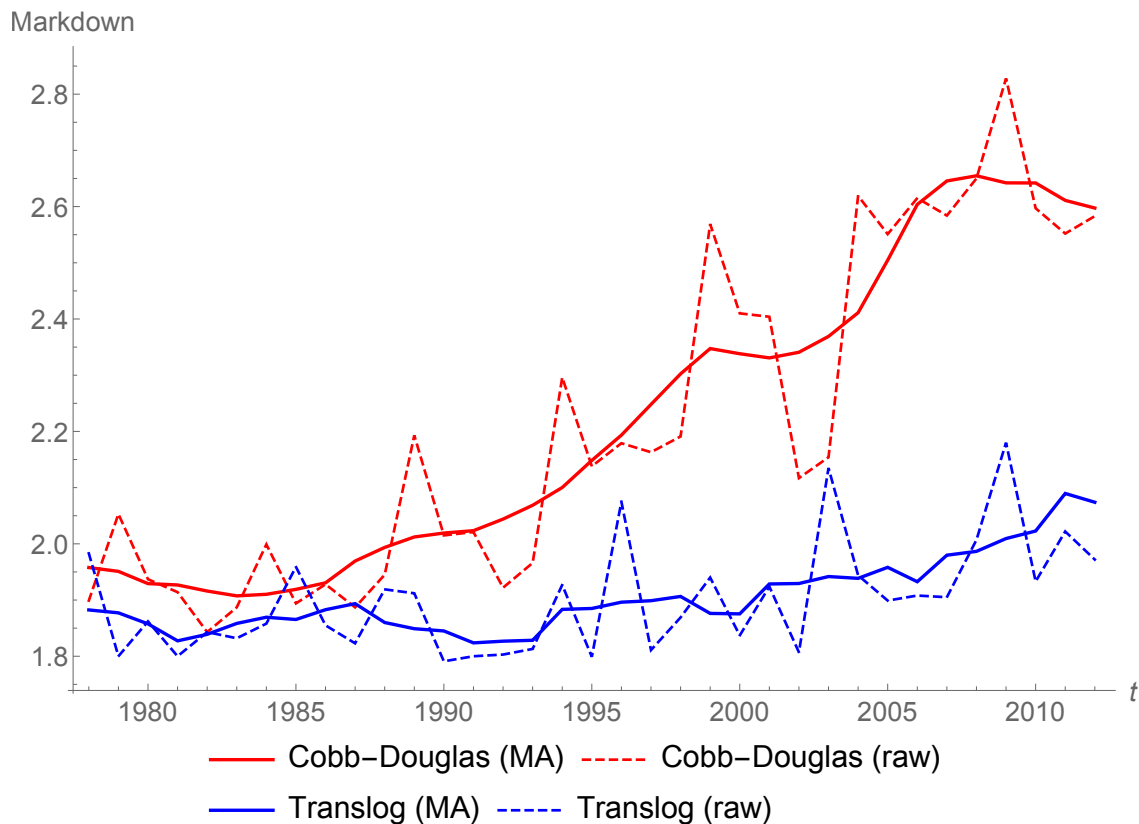
In addition to showing that markdowns are different from 1 in all U.S. manufacturing industries, we construct an aggregate index of markdowns as in equation (2) and document how it has changed over time. Figure 2 illustrates that employment-weighted averages of markdowns are increasing over time.<sup>4</sup> Our preferred specification uses a translog assumption for gross output and is depicted in the blue line. The red line in figure reflects the Cobb-Douglas specification.

The Cobb-Douglas specification assumes by construction that output elasticities are constant and, hence, ignores any time variation in a plant's output elasticities. This could potentially confound the positive, secular trend in markdowns. Indeed, we find that the Cobb-Douglas estimates show a larger increase: from 1.96 to

<sup>4</sup>These results do not change when we use total hours as weights instead.

2.60 since 1976. When we consider translog markdowns, instead, output elasticities are allowed to directly depend on a plant’s inputs and vary over time. While the increase in employment-weighted markdowns is not as stark as compared to the Cobb-Douglas estimates, they still increase from 1.89 to 2.07 over a period of almost 40 years. This is not a trivial increase: Eggertsson, Robbins and Wold (2018) have argued, for example, that secular increases in markups of this magnitude can explain a multitude of secular trends in the U.S. economy, so the implications for such an increase in markdowns are potentially just as relevant.

Figure 2: Time evolution of markdowns across U.S. manufacturing plants. The red lines illustrate markdowns estimated under a Cobb-Douglas production function (dashed line contains the raw time series; solid line is 3-year moving average). The blue lines illustrate markdowns estimated under a translog production function (again, dashed line is raw time series; solid line is a 3-year moving average). Markdowns appear to be trending upward over time, although this increase is much more stark for the Cobb-Douglas specification. Source: authors’ calculations from ASM/CM data in 1976–2014.



### 2.4.3 From markdowns to concentration

We have argued that estimating markdowns is a fruitful avenue to study of employer market power because markdowns are directly interpretable through basic economic principles and, in addition, the variation they display both in the cross-section and over time is informative on the extent of monopsony in the U.S. labor market. However, as evidenced in the previous sections, reliable estimates of markdowns build upon

the availability of detailed data on production inputs and output. Though such data is often available for manufacturing plants, both in the U.S. and other countries, the same level of detail does not extend to other sectors. This raises the problem of measuring employer market power *beyond* manufacturing. Often this goal is accomplished by proxying market power by concentration. Is this approach, and the tools commonly used within it, consistent with economic principles? How do measures of concentration relate to direct measure of market power? We now proceed to answer precisely these questions. Specifically, we empirically test the relationship between structural measures of employer market power, markdowns, and indirect measures based on firms' employment shares; notably concentration indexes such as the Herfindahl-Hirschman index or the CR measures popularized by Autor et al. (2017).

Intuitively, indexes of concentration based on firms' employment shares are indicative of employer market power whenever firms that are large in terms of employment are also those firms that set high markdowns. Going back to the formula for markdowns  $\mu = \frac{\varepsilon_S + 1}{\varepsilon_S}$  we see that, for this to be true, we require that a firm's labor supply elasticity  $\varepsilon_S$  is decreasing in a firm's size. While this insight in itself is not surprising, it is usually hard to verify this condition empirically. However, the first section of our paper is precisely dedicated to providing measures of markdowns at the micro-level. The next section will then introduce common indexes of concentration. Finally, section 4 will formally proceed to test the relationship between the two, that is between a firm's markdown and its size.<sup>5</sup>

### 3 Measures of employer market power: concentration

#### 3.1 Concentration indexes

The Herfindahl-Hirschman index (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, 2018 and Rossi-Hansberg, Sarte and Trachter, 2018).

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

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

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<sup>5</sup>If firms' labor supply elasticities are decreasing in their size, it can be argued that the measures of employment concentration are a reasonable measure for monopsony, as well. Obviously, the former still only functions as proxies for employer market power. We deem that they can nevertheless be informative. In particular, a few specific measures, like the Herfindahl-Hirschman index (HHI) are widely used by policy makers and facilitates comparison with the recent micro-literature on labor market concentration (such as Azar, Marinescu and Steinbaum (2017) and Benmelech, Bergman and Kim (2018)).

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. 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.

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.<sup>6</sup>

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 (so that a market  $m$  is an industry) and are then aggregated through employment or sales weights. Following Autor et al. (2017), we refer to these as measures of **national** concentration:

$$\begin{aligned} \text{NATIONAL}_t &= \sum_{j \in J} \omega_{jt} \text{HHI}_{jt} \\ &= \sum_{j \in J} \omega_{jt} \left[ \sum_{f \in F(j)} \left( \frac{x_{ft}}{X_{F(j)t}} \right)^2 \right] \quad \text{s.t.} \quad X_{F(j)t} = \sum_{f' \in F(j)} x_{f't} \end{aligned} \quad (7)$$

where  $F(j)$  denotes the set of firms in industry  $j$ . Outcomes  $x_{ft}$  and weights  $\omega_{jt}$  can be defined through either employment, payroll, vacancies, or sales. 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 et al. (2017) who define their HHIs through sales and employment whereas aggregation occurs in both cases through sales shares.<sup>7</sup>

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  $\ell$ , then an

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<sup>6</sup>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:

$$\text{CR}_{mt}^n = \sum_{f \in F(m;n)} \frac{x_{ft}}{X_{F(m)t}} \quad (6)$$

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

<sup>7</sup>Autor et al. (2017) also provide aggregate national concentration measures based on the industry-level prominence of the top 4 (or 20) firms:

$$\text{CR}_t^n = \sum_{j \in J} \omega_{jt} \sum_{f \in F(j;n)} \frac{x_{ft}}{X_{F(j)t}} \quad (8)$$

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

aggregate measure of **local** concentration is:

$$\begin{aligned} \text{LOCAL}_t &= \sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} \text{HHI}_{j\ell t} \\ &= \sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} \left[ \sum_{f \in F(j,\ell)} \left( \frac{x_{f\ell t}}{X_{F(j,\ell)t}} \right)^2 \right] \quad \text{s.t.} \quad X_{F(j,\ell)t} = \sum_{f' \in F(j,\ell)} x_{f'\ell t} \end{aligned} \quad (9)$$

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 (9) 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 and vacancies to explore different approaches to computing aggregate labor market concentration and relate them to each other.<sup>8</sup>

### 3.2 Data: BGT and LBD

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

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 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).<sup>9</sup> 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

<sup>8</sup>Results using job creation flows, payroll and sales are awaiting disclosure.

<sup>9</sup>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.

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.<sup>10</sup> 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).<sup>11</sup>

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 (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. 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 The scope of a labor market

In order to compute an index of concentration, we must first define the *scope* of a labor market, i.e. the boundaries of it. In this paper, we characterize a local labor market as a sector-location pair. In the BGT

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<sup>10</sup>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.

<sup>11</sup>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.



data, we define a local labor market as an occupation-metro area pair. Information on occupation and metro areas is not standardly available in the LBD data, so we approximate it using industry-county pairs.<sup>12</sup>

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.<sup>13</sup> 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 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.<sup>14</sup> There are more than 1,000 counties that satisfy this requirement in the U.S. as per the 2013 Census delineations.

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<sup>12</sup>Our results are robust to defining local labor markets in the LBD as an industry-metro area pair, but details are pending disclosure.

<sup>13</sup>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).

<sup>14</sup>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.

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).<sup>15</sup> Summary statistics for job creation and payroll are awaiting disclosure.

### 3.4 Labor market concentration in the U.S.

#### 3.4.1 Cross-sectional distribution

In this section, we analyze the cross-sectional properties of concentration in employment and vacancies. The main take-away is that we do not find evidence of widespread concentration in employment nor vacancy flows. On the other hand, we show that concentrated markets are small and their employer mix is skewed toward large national firms that are active across multiple regions.

Table II: 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           |

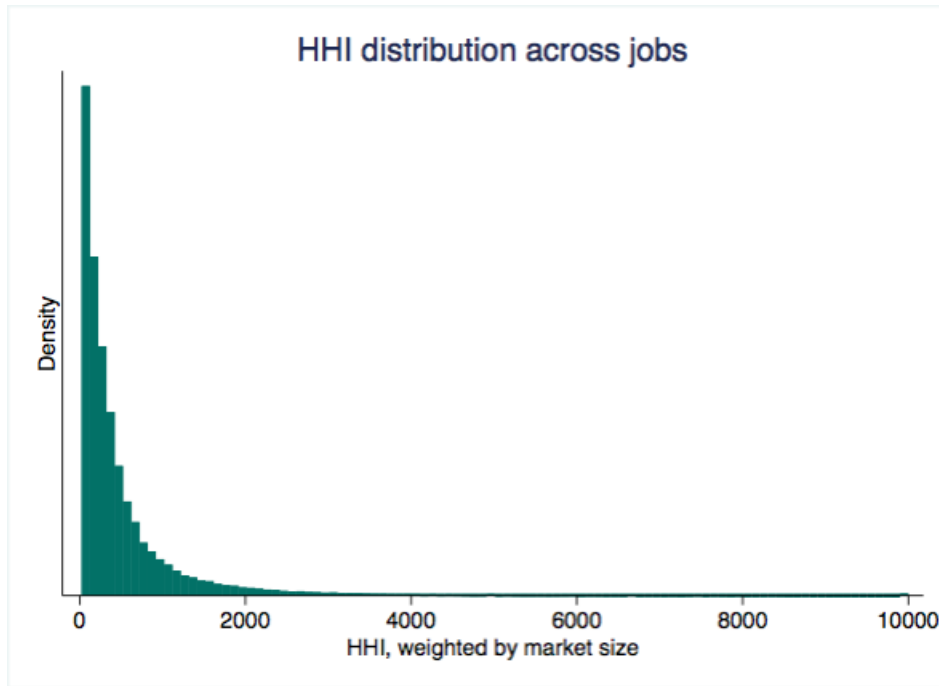
Employment stock is more concentrated than job postings flow, but only markets above the 75<sup>th</sup> percentile are “moderately concentrated” according to DOJ guidelines (HHI > 0.25). All markets are weighted by their size. Source: BGT, LBD.

Table II 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.<sup>16</sup> 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 3 depicts the full distribution for the HHI of job postings. The figure has

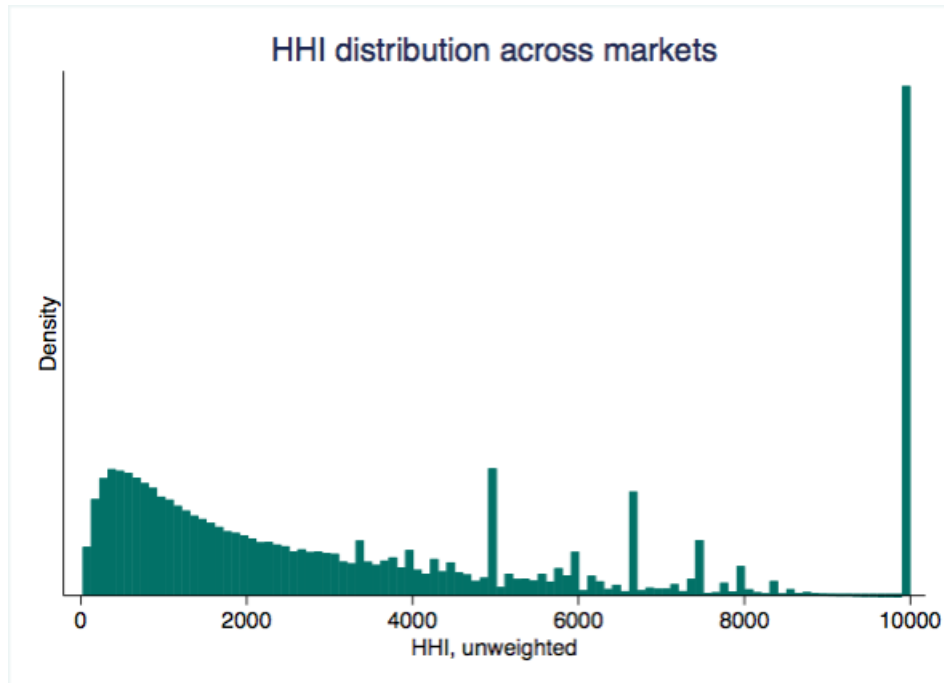
<sup>15</sup>Numbers are rounded as per the Census Bureau’s disclosure rules.

<sup>16</sup>The official threshold for concentrated markets in the product market is a HHI of sales greater or equal than 2500.

Figure 3: Local HHI distribution of job postings from 2007 - 2017. Source: BGT.



(a) Weighted by market size



(b) Unweighted

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 and workers per year is negatively correlated with the level of concentration. Table III displays statistics from BGT and LBD that illustrate this result: in first and second rows of the top panel, we compute the total number of postings per year by quartiles of concentration. Markets in the highest concentration quartiles post on average 23 jobs per year, in contrast with 596 job ads per year in the least concentrated markets. A similar patterns holds for the number of workers.

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

| (yearly medians)        | <i>Market's rank in concentration distribution</i> |              |              |              |
|-------------------------|--|--------------|--------------|--------------|
|                         | 1st quartile                                       | 2nd quartile | 3rd quartile | 4th quartile |
| vacancies per market    | 596  | 171          | 77           | 23           |
| workers per market      | 3,200  | 1,500        | 650          | 200          |
| city size               | 822,007  | 447,774      | 368,849      | 362,460      |
| workers per firm        | <15  | <15          | 20           | 30           |
| vacancies per firm      | 84   | 125          | 155          | 173          |
| workers per firm-county | <15  | <15          | <15          | <15          |
| vacancies per firm-MSA  | 5  | 5            | 5            | 5            |
| yearly income           | 48,000   | 32,000       | 28,600       | 30,000       |
| % part-time             | 0.12   | 0.20         | 0.25         | 0.22         |
| educ. years             | 15.00  | 13.00        | 13.00        | 13.00        |
| unempl. rate            | 0.08   | 0.08         | 0.08         | 0.08         |
| vac. per worker         | 0.19   | 0.11         | 0.13         | 0.12         |
| tightness               | 2.33   | 1.43         | 1.50         | 1.44         |

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 first and second rows of the second panel in table III. 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.<sup>17</sup> 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

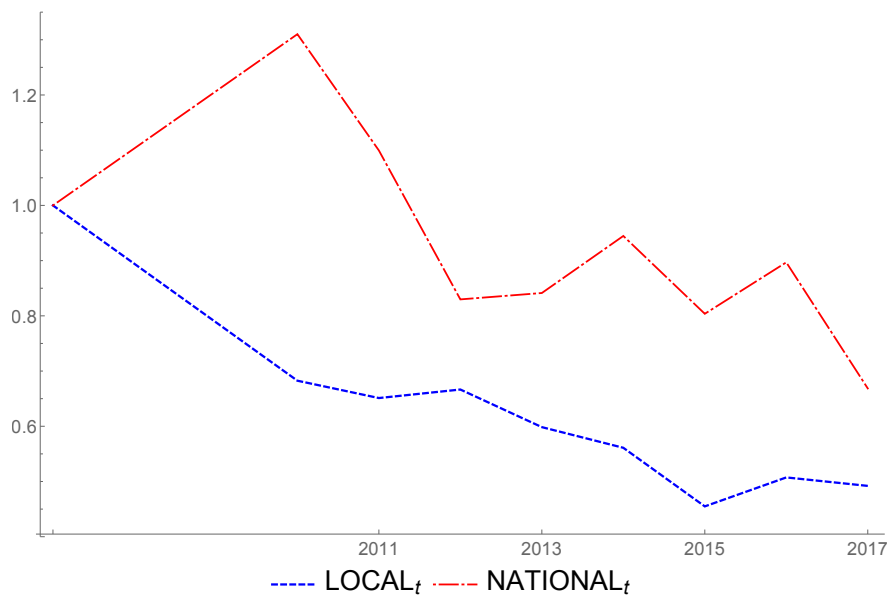
<sup>17</sup>Local branches of these employers are not necessarily larger however: the number of postings per employer–metro-area–year does not vary with labor market concentration (row 4 and 5, panel 2, in table III).

of smaller firms instead.

### 3.4.2 Trends

**VACANCIES.** We regard vacancies concentration as the closest measure to the concentration faced by job seekers in a specific (local or national) labor market. We construct concentration measures of vacancies (job postings) following (7) and (9) and using BGT data. Market-level HHIs are aggregated through their respective vacancy shares.<sup>18</sup> Figure 4 plots the time series of the aggregate local and national 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. While the pattern is not as clear for national concentration, figure 4 does clearly show that the decline in local concentration is much stronger than its national counterpart.

Figure 4: 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. Observations from the Great Recession (2008–2009) are not available and are interpolated from 2007 to 2010.

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.

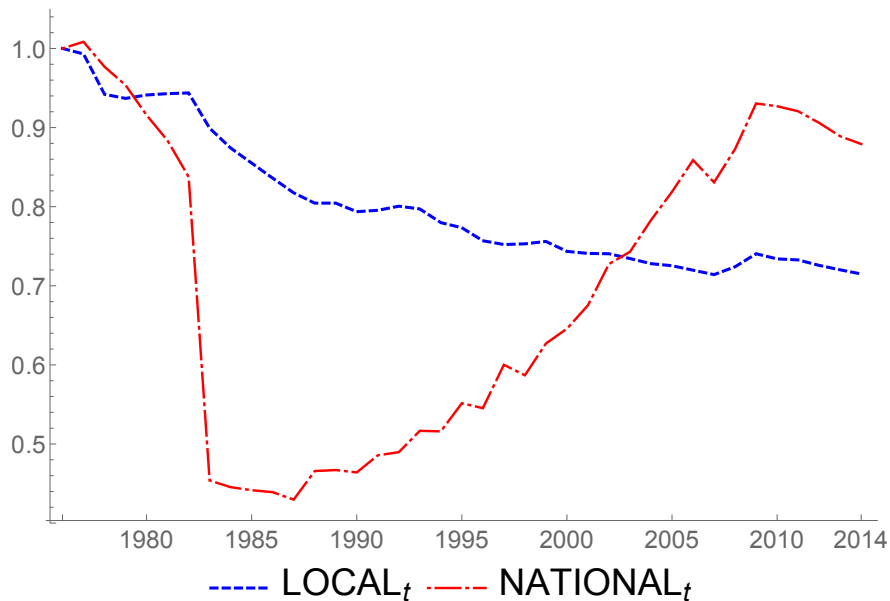
**EMPLOYMENT.** In figure 5, we construct national and local concentration measures for the stock of em-

<sup>18</sup>Our results are quantitatively unaffected whenever we use employment shares instead.

ployment. Employment also functions as the size of a market and markets are thus aggregated through employment shares. As can be seen in figure 5, 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.

The results for national employment concentration show a stark contrast: it has been increasing from 1983 onward.<sup>19</sup> Furthermore, this increase is quite sizable as national concentration has almost doubled since the 1983. Our results are consistent with Autor et al. (2017) who find that national sales concentration has been on the rise since the mid 1980s for most industries. Moreover, Rinz (2018) and Rossi-Hansberg, Sarte and Trachter (2018) also document a divergent pattern between national and local employment concentration using administrative data and the NETS database, respectively.

Figure 5: National and local trends in the concentration of employment. Source: LBD.



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

We conclude that there is a diverging trend between national and local employment concentration, similar to what has been found for sales. How to interpret this apparently contradictory evidence? In the following section, we argue that such pattern can be rationalized by factoring in the spatial behavior of firms and a decrease in spatial dispersion in employment across U.S. local labor markets.

<sup>19</sup>The artificial downward spike from 1982 to 1983 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.

### 3.4.3 Reconciling national and local trends in concentration

In the previous section, we computed the time series for several measures of labor market concentration — the HHIs of employment and vacancy flows — and find that national labor market concentration has increased since the early 1980s, while local labor market concentration has diminished substantially since the late 1970s.

While these empirical facts seem contradictory at first, we show that they are not. In fact, we derive several conditions 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 sector-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  $j$ ,  $\ell$  and  $t$  denote industries, locations and years, respectively. Then, aggregate local concentration can be decomposed as follows:

$$\begin{aligned}
\sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} HHI_{j\ell t} &= \sum_{j \in J} \omega_{jt} \left[ \sum_{\ell \in L} \frac{\omega_{j\ell t}}{\omega_{jt}} HHI_{j\ell t} \right] \\
&= \sum_{j \in J} \omega_{jt} \left[ \sum_{\ell \in L} s_{\ell t}^j HHI_{j\ell t} \right] \\
&= \sum_{j \in J} \omega_{jt} \left[ \overline{HHI}_{jt} + cov(s_{\ell t}^j, HHI_{j\ell t}) \right] \\
&= \sum_{j \in J} \omega_{jt} HHI_{jt} + \sum_{j \in J} \omega_{jt} cov(s_{\ell t}^j, HHI_{j\ell t}) - \sum_{j \in J} \omega_{jt} (HHI_{jt} - \overline{HHI}_{jt}) \quad (10)
\end{aligned}$$

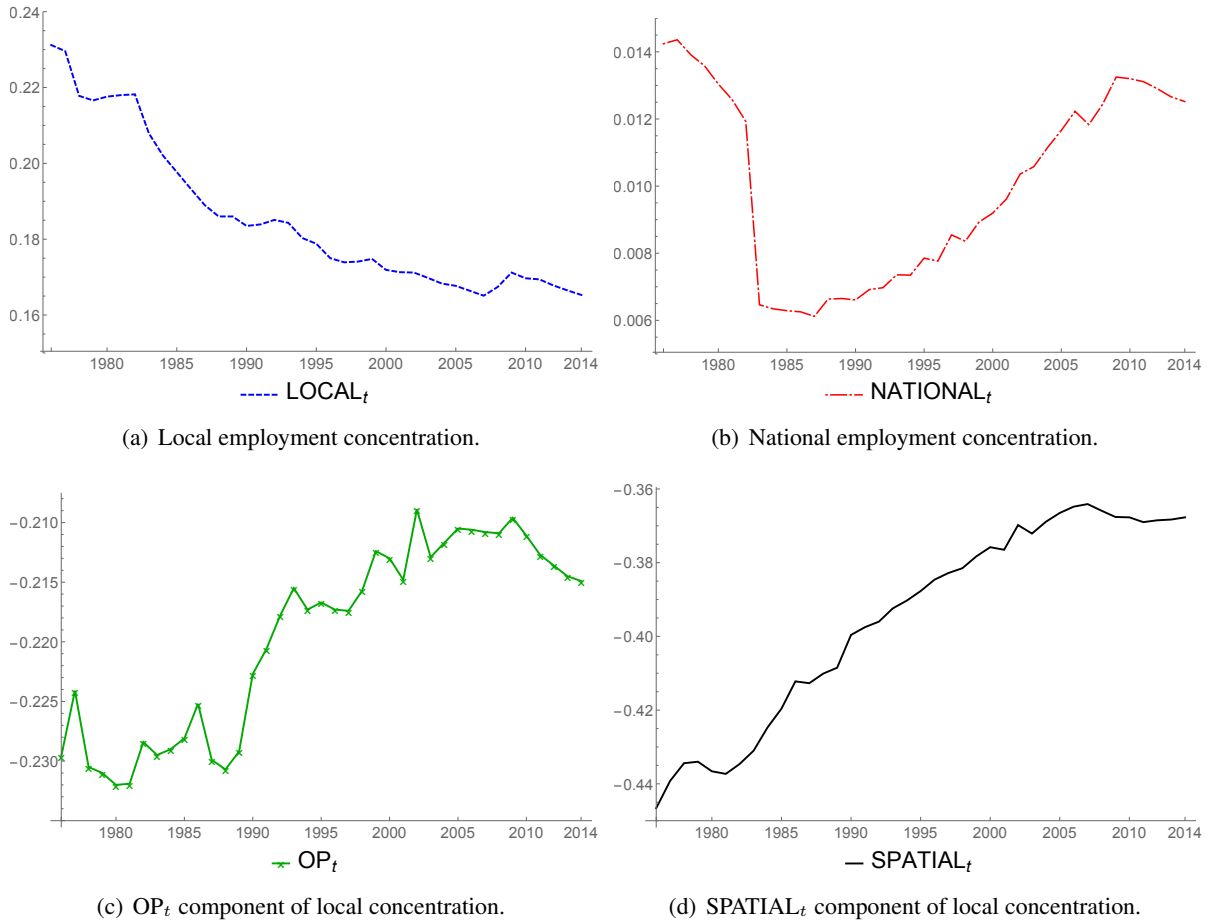
where  $\overline{HHI}_{jt} \equiv \frac{1}{|L|} \sum_{\ell \in L} HHI_{j\ell t}$  is the unconditional mean of HHI across locations in a given industry  $j$  and year  $t$ . In the following, we will denote  $OP_t \equiv \sum_{j \in J} \omega_{jt} cov(s_{\ell t}^j, HHI_{j\ell t}) - \sum_{j \in J} \omega_{jt} (HHI_{jt} - \overline{HHI}_{jt})$  and  $SPATIAL_t \equiv \sum_{j \in J} \omega_{jt} (HHI_{jt} - \overline{HHI}_{jt})$ . Following our definitions of national and local concentration in (7) and (9), we can therefore write our decomposition in (10) as:

$$LOCAL_t = NATIONAL_t + OP_t - SPATIAL_t \quad (11)$$

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 the “spatial composition” of employment.

To understand this spatial term better, it is helpful to analyze its corner cases. In the appendix, we show that  $SPATIAL_t$  is contained in the interval  $[-1, 1]$ . Intuitively, the term  $SPATIAL_t$  is equal to  $-1$  whenever each local labor market features a monopsonist but none of these employers is large relative to the aggregate. Its polar case of  $SPATIAL_t = 1$  is achieved whenever there is exactly one monopsonistic local labor market and its respective employer is large relative to the aggregate. As a result, the term  $SPATIAL_t$  reflects the composition of employment across space as it varies from a scenario in which no monopsony matters for aggregate outcomes to a composition in which the aggregate is dominated by exactly one monopsonist. The intermediate value of  $SPATIAL_t = 0$  can also be interpreted economically. Under this scenario, employment is perfectly distributed across space, i.e. each firm is active in each local labor market with the same amount of employees. Thus, this means there is no spatial dispersion in terms of employment.

Figure 6: Decomposition of local concentration from 1976–2014. Source: LBD.



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) a spatial composition of employment that is diverging from a setting in which there are many small local monopsonies. 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. Note that the covariance between market size and concentration at the local level involves the share of a local labor



market’s employment relative to the industry.<sup>20</sup>

Figure 6 displays the results of decomposition (10). Our results imply that the divergence in local and national concentration can only be explained by the spatial component. This is because the covariance term  $OP_t$  moves in the opposite direction (i.e., increasing over time) of what is required. On the other hand, we observe that the spatial term  $SPATIAL_t$  is increasing over time by about 8 percentage points which is roughly the same amount by which local and national concentration have diverged. Lastly, the spatial component has converged towards zero from below which indicates that the U.S. economy is converging towards a spatial structure that displays less and less dispersion.

While there are different approaches to reconcile the diverging trend between national and local concentration (see, for example, the “top firms” narrative in Rossi-Hansberg, Sarte and Trachter, 2018), the use of decomposition (10) for this particular purpose has several advantages. First, it relates local and national concentration in a transparent fashion. In particular, decomposition (10) highlights through what forces national and local concentration can diverge; be it through a mechanism that pushes down the covariance between a size’s market and concentration, and/or a narrative that changes the spatial composition of employment. Interestingly, the mechanism put forth by Rossi-Hansberg, Sarte and Trachter (2018) is fully consistent with a spatial component that is increasing over time. Second, our decomposition can be applied industry-by-industry and is clear on aggregation across industries. The contribution of each industry’s covariance or spatial component in explaining the divergence between local and national concentration is simply summarized by its employment share  $\omega_{jt}$ . Therefore, we can also investigate whether the observed diverging trends are partly due to industry composition.

## 4 Relationship between markdowns and concentration

What is the relationship between markdowns — a direct measure of employer market power — and concentration?<sup>21</sup> In this section, we offer explicit conditions under which the HHI, and any index based on firms’ shares of market-level employment, is not only a natural measure for labor market concentration but also a suitable measure for employers’ market power.

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<sup>20</sup>This is not the same as the covariance between a local labor market’s size *relative to the aggregate* and its concentration. In fact, it can be shown that:

$$\begin{aligned} OP_t &= \sum_{j \in J} \omega_{jt} cov(s_{jt}^j, HHI_{j\ell t}) \\ &= cov(\omega_{j\ell t}, HHI_{j\ell t}) - \sum_{j \in J} \left( \omega_{jt} - \frac{1}{|J|} \right) \overline{HHI}_{jt} \end{aligned} \quad (12)$$

Thus, it is important to note whether a market’s size is defined relative to its industry or the aggregate as the time trend for each of these covariances could be moving in opposite directions.

<sup>21</sup>Azar, Marinescu and Steinbaum (2017) argue that an advantage of the HHI measure is that there are guidelines specified by the DOJ/FTC that determine what constitutes a “concentrated” market. While we recognize that these guidelines are informative, in this section we illustrate the relationship between concentration and monopsony in a more rigorous fashion using an approach in the spirit of De Loecker and Eeckhout (2017).

The Herfindahl-Hirschman index based on employment is a natural measure of labor market concentration. By construction, it captures the presence of relatively large employers in a given market. While it seems intuitive that large employers possess the most labor market power, it cannot be ruled out ex-ante that market power and concentration are negatively correlated. As Syverson (2019) points out for output markets, this negative correlation is not “just a theoretical curiosity” (as can be, for example, seen in the framework of Melitz and Ottaviano (2008)) since there are numerous empirical studies indicating that such a negative relationship is actually observed in the data (see Syverson, 2004a; Syverson, 2004b; Goldmanis et al., 2010).<sup>22</sup> Therefore, some caution should be exercised when measures of concentration are used as proxies for market power.

By construction, the employment HHI of an industry captures the degree to which that industry is populated by relatively large employers. Assuming that firms’ markdowns are perfectly proportional to their relative size requires specific and stringent functional form assumptions on a firm’s production technology and the preference structure of workers. Therefore, we argue for a weaker condition: that markdowns are increasing in a firm’s 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 establish whether markdowns increase with a firm’s employment share (that is, when a firm’s perceived labor supply elasticity is decreasing in its size).

Our estimates for plant-level markdowns and employment shares — detailed in section 2 and 3 — allow us to test this hypothesis in the data directly. To do so, we run the following regression:

$$\ln(\mu_{it}) = \beta_0 + \beta_1 \cdot \ln(s_{it}) + \mathbf{X}'_{it}\gamma + \varepsilon_{it} \quad (13)$$

where  $\mu_{it}$  denotes a plant  $i$ ’s markdown in year  $t$ ,  $s_{it}$  is the plant’s employment share in its local labor market and  $\mathbf{X}_{it}$  contains a set of controls. These controls consist of fixed effects for the detailed industry, county-year, and the age of a plant. To confirm our hypothesis, we require positive estimates on a plant’s employment share, i.e.  $\beta_1 > 0$ .

Table IV confirms the positive relationship between markdowns and employment share. In our preferred specification with translog markdowns, we find positive and significant size elasticities. The results are qualitatively unaffected whenever we estimate semi-elasticities instead. While we observe similar results for markdowns under a Cobb-Douglas specification, the results are somewhat noisier. Our estimates imply that a one standard deviation change in local labor market employment shares increases markdowns by 3.7% on average.

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<sup>22</sup>In fact, the so-called structure-conduct-performance literature was basically halted because of the fact that the correlation between market power and concentration is ex-ante unclear.

Table IV: Estimation results of relationship between plant-level markdowns and size.<sup>b</sup>

| Dependent variable: PLANT-LEVEL MARKDOWNS |                      |                       |
|---|----------------------|-----------------------|
|   | Cobb-Douglas         | Translog              |
| NATURAL LOG SHARE                         | 0.0292**<br>(0.0140) | 0.0251***<br>(0.0052) |
| SHARE                                     | 0.1418**<br>(0.0649) | 0.1363***<br>(0.0335) |
| Observations (in millions)                | 1.449                | 1.449                 |

<sup>b</sup>U.S. manufacturing industries for years 1976–2014. The independent variable is the natural log of markdowns under the assumption of a Cobb-Douglas or translog specification for gross output. All regression specifications include industry, county-year fixed effects, and age controls. Standard errors are clustered at the industry (3-digit NAICS) level.

## 5 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”.

### 5.1 Wages

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

$$\ln(\bar{w}_{mt}) = \mu + \gamma \cdot \ln(HHI_{mt}) + \mathbf{X}'_{mt}\beta + \varepsilon_{mt} \quad (14)$$

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.

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

|                       | (1)           | (2)           | (3)           |
|-----------------------|---------------|---------------|---------------|
| <b>log(HHI)</b>       | <b>-0.012</b> | <b>-0.014</b> | <b>-0.050</b> |
|                       | (10.99)       | (7.43)        | (9.97)        |
| log(HHI) <sup>2</sup> | –             | –             | 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                | –             | ✓             | ✓             |
| <i>N</i>              | 371,304       |               |               |

As depicted in table V, 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 (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.

Table VI: Increases in the local HHI are associated with decreases in wages concentrated among college-educated workers.

|                                  | (1)           | (2)           |
|----------------------------------|---------------|---------------|
| <b>log(HHI)</b>                  | <b>-0.010</b> | 0.014         |
|                                  | (0.002)       | (0.006)       |
| log(HHI)*HS                      | –             | -0.007        |
|                                  |               | (0.007)       |
| log(HHI)*SC                      | –             | -0.013        |
|                                  |               | (0.007)       |
| <b>log(HHI)*C</b>                | –             | <b>-0.033</b> |
|                                  |               | (0.010)       |
| log(city size)                   | 0.758         | 0.253         |
|                                  | (0.083)       | (0.091)       |
| log(tightness)                   | 0.335         | 0.312         |
|                                  | (0.086)       | (0.073)       |
| log(remoteness)                  | -0.073        | -0.075        |
|                                  | (0.031)       | (0.026)       |
| <hr/> <i>N</i> = 3,932,553 <hr/> |               |               |

Lastly, we run a regression similar to (14) but use worker-level data from the American Community Survey (ACS) instead. This approach does not only allow us to control for worker-level characteristics, but it also enables us to investigate whether the effect of concentration on wages is heterogeneously borne across workers of different types. In particular, we focus on workers with different levels of education: less than a high school degree, high school degree completed (HS), some college attendance but no degree (SC) and college degree (C). The results are displayed in table VI below.

If we impose that the wage compression effects of concentration are homogeneous across workers, then we obtain similar results to our preferred specification in table V (column 2). However, the second column of table VI implies that these effects are far from homogeneous. In fact, our results indicate that the wage compression effects are only significant for college-educated workers. This suggests that policy interventions predicated on raising the minimum wage in response to monopsony are likely to have minimal to no effects — most college-educated workers are not constrained by the minimum wage threshold.

## 5.2 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.

### 5.2.1 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.<sup>23</sup> 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," 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).

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<sup>23</sup>We plan to add education and experience requirements, as in Hershbein and Kahn (2018), in the near future.

Table VII: 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++)                 |

Table VIII: 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      |

### 5.2.2 Descriptive analysis: the skill content of jobs

We characterize firm-level skill demand in each market by counting how many job postings require each of the five skill categories 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 doing so, we capture the extensive margin of skill demand within a given job posting, rather than the intensive margin. Many employer-market-year cells do not have any ads listing a specific skill category (see table VIII). That said, social skills are the most frequently requested while specialized computer skills are the least.

### 5.2.3 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:

$$\# \text{ mentions skill } s_{fmt} = \mu + \gamma \cdot \ln(HHI_{mt}) + \mathbf{X}_{mt}^l \beta + \varepsilon_{fmt} \quad (15)$$

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.

Table IX: 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><br>(28.74) | <b>0.104</b><br>(34.65) | <b>0.117</b><br>(40.78) | <b>0.064</b><br>18.97 | <b>0.064</b><br>(28.91) | <b>0.070</b><br>26.47 |
| log(labor force)          | 0.245<br>(60.32)        | 0.216<br>(38.65)        | –                       | 0.183<br>(50.30)      | 0.141<br>(28.91)        | –                     |
| log(college share)        | 0.206<br>(24.61)        | 0.168<br>(21.51)        | –                       | 0.179<br>(20.22)      | 0.142<br>(19.17)        | –                     |
| log(unempl. rate)         | 0.008<br>(1.30)         | -0.040<br>(-6.73)       | –                       | 0.015<br>(2.60)       | -0.031<br>(-5.76)       | –                     |
| mkt size                  | –                       | 0.0001<br>(8.49)        | 0.0001<br>(8.46)        | –                     | 0.0001<br>(8.72)        | 0.0001<br>(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



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 IX and X. In table IX, 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 (15), 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 VIII). 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 IX 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 ( $\gamma$ ) 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:

$$\# \text{ mentions skill } s_{fmt} = \mu + \alpha_f + \alpha_{o(m)} + \alpha_{c(m)} + \alpha_t + \gamma \cdot \ln(HHI_{mt}) + \varepsilon_{fmt} \quad (16)$$

We use this specification to investigate how labor market concentration affects the demand for different types of skills. Figure 7 shows the equivalent of regression (16) 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.

Table X: 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<br>(40.78)  | 0.115<br>(38.65) | 0.070<br>(26.47)   | 0.068<br>(24.60) | 0.077<br>(36.82) | 0.076<br>(35.19) |
|                           | Computer, general |                  | Computer, specific |                  | Any computer     |                  |
| log(HHI)                  | 0.049<br>(31.97)  | 0.048<br>(30.30) | 0.018<br>(4.34)    | 0.017<br>(4.05)  | 0.060<br>(15.32) | 0.059<br>(14.35) |
| Employer FE               | ✓                 | ✓                | ✓                  | ✓                | ✓                | ✓                |
| Occupation FE             | ✓                 | ✓                | ✓                  | ✓                | ✓                | ✓                |
| Year FE                   | ✓                 | ✓                | ✓                  | ✓                | ✓                | ✓                |
| MSA FE                    | ✓                 | ✓                | ✓                  | ✓                | ✓                | ✓                |
| Excludes HHI $\geq$ 5000  | No                | Yes              | No                 | Yes              | No               | Yes              |
| <i>N</i>                  | 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.

#### 5.2.4 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.<sup>24</sup>

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

<sup>24</sup>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.

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.

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

|                           | Social            | Cognitive          | Organizational   |
|---------------------------|-------------------|--------------------|------------------|
| high-skill                | 0.081<br>(19.36)  | 0.045<br>(11.10)   | 0.061<br>(24.84) |
| low-skill                 | 0.131<br>(36.99)  | 0.093<br>(27.10)   | 0.064<br>(28.65) |
|                           | Computer, general | Computer, specific | Any computer     |
| high-skill                | 0.375<br>(22.25)  | 0.010<br>(1.79)    | 0.044<br>(8.46)  |
| low-skill                 | 0.0397<br>(20.20) | 0.026<br>(5.70)    | 0.057<br>(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.

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 (16) 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 XI, 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 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.

## 6 Conclusion

This paper makes three main contributions: first, it estimates markdowns and concentration indexes in U.S. administrative data and characterizes their cross-sectional distributions and time-series behavior. We estimate markdowns using an empirical strategy that exploits well-established methods in the markup estimation literature and applies them to the estimation of markdowns. We find that the average U.S. manufacturing plant has a markdown of 68%, but there is substantial heterogeneity even within narrow industries. Furthermore, the aggregate markdown rate has increased over time by approximately 10% since 1976.

Given the stringent data requirement inherent in markdowns estimation, we turn our attention to a popular measure of concentration, the Herfindahl-Hirschman Index. We use data on the universe of online vacancies (BGT) and the universe of employers (LBD), from which we compute concentration in the employment stock and vacancy flow. 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, while *national* labor market concentration has increased. We reconcile these diverging trends through a statistical decomposition which implies a drop in the spatial dispersion of employment across U.S. local labor markets.

Our second contribution is to explicitly set out the conditions under which indexes of concentration based on firms' employment shares, such as the HHI, are a good proxy for monopsony power. Specifically, we show that HHIs 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 — hence the condition that markdowns are positively correlated with size. Regressing our estimated markdowns on employment shares from the data, we find that this condition is verified.

Finally, our third contribution looks at the relationship between concentration and (i) wages, (ii) skill demand. Indeed, 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. 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 Bounds of spatial component

### A.1 Small local monopsonies

Each firm operates as a local monopsonist. However, none of the monopsonists is large relative to the aggregate. The latter can be achieved in a symmetric setup with a large number of firms.

| REGION/FIRM | 1   | 2   | ...      | $n-1$    | $n$      |
|-------------|-----|-----|----------|----------|----------|
| 1           | $a$ | 0   | ...      | 0        | 0        |
| 2           | 0   | $a$ | ...      | 0        | 0        |
| $\vdots$    | 0   | 0   | $\ddots$ | $\vdots$ | $\vdots$ |
| $m-1$       | 0   | 0   | ...      | $a$      | 0        |
| $m$         | 0   | 0   | ...      | 0        | $a$      |

$$HHI_j = \sum_{i=1}^n \left( \frac{a}{n \cdot a} \right)^2 = \frac{1}{n}$$

$$\overline{HHI}_j = \frac{1}{m} \sum_{i=1}^m \frac{a}{a} = 1$$

$$\lim_{n \rightarrow +\infty} \text{SPATIAL}_j = \lim_{n \rightarrow +\infty} \left( \frac{1}{n} - 1 \right) = -1$$

### A.2 Perfect spatial dispersion

In this setup, employment is perfectly dispersed across firms in each local market. This example is independent of the number of markets  $m$  and firms  $n$ .

| REGION/FIRM | 1   | 2   | ...      | $n-1$    | $n$      |
|-------------|-----|-----|----------|----------|----------|
| 1           | $a$ | $a$ | ...      | $a$      | $a$      |
| 2           | $a$ | $a$ | ...      | $a$      | $a$      |
| $\vdots$    | $a$ | $a$ | $\ddots$ | $\vdots$ | $\vdots$ |
| $m-1$       | $a$ | $a$ | ...      | $a$      | $a$      |
| $m$         | $a$ | $a$ | ...      | $a$      | $a$      |

$$HHI_j = \sum_{i=1}^n \left( \frac{ma}{n \cdot ma} \right)^2 = \frac{1}{n}$$

$$\overline{HHI}_j = \frac{1}{m} \sum_{i=1}^m \frac{a}{n \cdot a} = \frac{1}{n}$$

$$\text{SPATIAL}_j = 0, \text{ for all } n > 1$$

### A.3 Dominating local monopsony

In this setup, there is exactly one local monopsonist and this monopsony is large relative to the aggregate. In particular, suppose firm  $K$  dominates the country by being a monopsonist in some market  $r$ : it has  $a = \alpha \cdot mn$  employees for some large  $\alpha > 1$ . The latter coefficient means that firm  $K$  is  $\alpha$  times larger than the whole, remaining stock of employment in the country. For simplicity, we assume that each firm has exactly one employee in each market.

| REGION/FIRM | $K$      | 1 | 2 | ...      | $n-1$    | $n$      |
|-------------|----------|---|---|----------|----------|----------|
| $r$         | $a$      | 0 | 0 | ...      | 0        | 0        |
| 1           | 0        | 1 | 1 | ...      | 1        | 1        |
| 2           | 0        | 1 | 1 | ...      | 1        | 1        |
| $\vdots$    | $\vdots$ | 1 | 1 | $\ddots$ | $\vdots$ | $\vdots$ |
| $m-1$       | 0        | 1 | 1 | ...      | 1        | 1        |
| $m$         | 0        | 1 | 1 | ...      | 1        | 1        |

$$HHI_j = \left( \frac{a}{a + m \cdot n} \right)^2 + \sum_{i=1}^n \left( \frac{m}{a + m \cdot n} \right)^2 = \left( \frac{a}{a + m \cdot n} \right)^2 + n \left( \frac{m}{a + m \cdot n} \right)^2$$

$$\overline{HHI}_j = \frac{1 + m \cdot \left[ \sum_{i=1}^n \left( \frac{1}{n} \right)^2 \right]}{m + 1} = \frac{1}{m + 1} + \frac{m}{m + 1} \cdot \frac{1}{n}$$

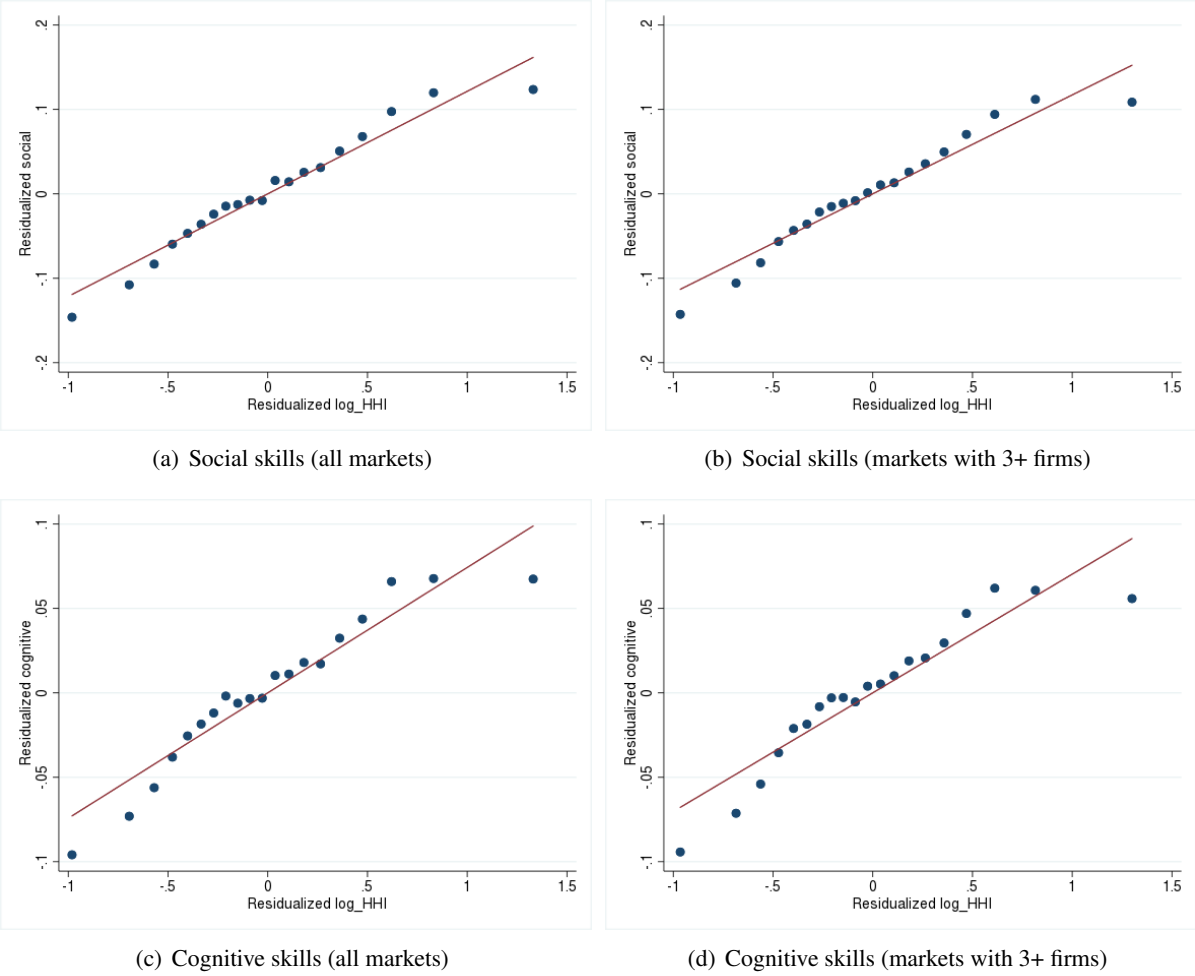
$$\begin{aligned} \text{SPATIAL}_j &= \left( \frac{\alpha}{1 + \alpha} \right)^2 + \frac{1}{n} \left( \frac{m \cdot n}{a + m \cdot n} \right)^2 - \frac{1}{m + 1} - \frac{m}{m + 1} \cdot \frac{1}{n} \\ &= \left( \frac{\alpha}{1 + \alpha} \right)^2 + \frac{1}{n} \left( \frac{1}{\alpha + 1} \right)^2 - \frac{1}{m + 1} - \frac{m}{m + 1} \cdot \frac{1}{n} \end{aligned}$$

$$\lim_{m, n \rightarrow +\infty} \text{SPATIAL}_j = \left( \frac{\alpha}{1 + \alpha} \right)^2$$

Then, we can make  $\text{SPATIAL}_j$  arbitrarily close to unity by picking a sufficiently large  $\alpha > 1$ . More precisely, we have  $\lim_{m, n, \alpha \rightarrow +\infty} \text{SPATIAL}_j = +1$ .

# B Skill regressions: non-linearities

Figure 7: The positive relationship between labor market concentration and skill demand.



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