Labor Market Concentration*

JOSÉ AZAR — IESE Business School & CEPR

IOANA MARINESCU — University of Pennsylvania & NBER

MARSHALL STEINBAUM — University of Utah

Abstract

A product market is concentrated when a few firms dominate the market. Similarly, a labor market is concentrated when a few firms dominate hiring in the market. Using data from the leading employment website CareerBuilder.com, we calculate labor market concentration for over 8,000 geographic-occupational labor markets in the US. Based on the DOJ-FTC horizontal merger guidelines, the average market is highly concentrated. Going from the 25th percentile to the 75th percentile in concentration is associated with a 5% (OLS) to 17% (IV) decline in posted wages, suggesting that concentration increases labor market power.

Keywords: Monopsony, Oligopsony, Labor Markets, Competition Policy

*Azar: Assistant Professor at the University of Navarra's Business and Economics Department and a Visiting Assistant Professor and Ressearch Associate at Unversity of Navarra's IESE Business School IESE Business School, Av Pearson, 21, 08034 Barcelona, Spain. CEPR Associate. jazar@iese.edu. Marinescu: Assistant Professor at University of Pennsylvania School of Social Policy & Practice, 3701 Locust Walk, Philadelphia PA, 19104-6214, ioma@upenn.edu. NBER Faculty Researh Fellow. Steinbaum: Assistant Professor at University of Utah Economics Department, 260 Central Campus Dr 4100, Salt Lake City, UT 84112. José Azar gratefully acknowledges the financial support of Secretaria d'Universitats I Recerca del Departament d'Empresa I Coneixement de la Generalitat de Catalunya. Ref.2016 BP00358. Marshall Steinbaum gratefully acknowledges the financial support of the Ewing Marion Kauffman Foundation. This paper uses proprietary data from CareerBuilder.com. We thank Jonathan Baker, Einer Elhauge, Hiba Hafiz, Larry Katz, Alan Krueger and Michael Ransom for helpful comments.

doi:10.3368/jhr.monopsony.1218-9914R1

1 Introduction

There is growing concern about increasing market concentration and its potential effects on the economy, including increases in markups (De Loecker and Eeckhout, 2017) and the decline in the labor share (Autor et al., 2019; Barkai, 2016). Concerns about a lack of competition in the labor market have also reached the policy debate (CEA, 2016). While interest in monopsony has grown in recent years (Ashenfelter, Farber and Ransom, 2010; Manning, 2011; Staiger, Spetz and Phibbs, 2010; Falch, 2010; Ransom and Sims, 2010; Matsudaira, 2013), this empirical work has generally focused on particular labor markets. Therefore it is not clear how widespread labor market power truly is, and how much it affects wages.

In this paper, we approach this question by directly quantifying the level of labor market concentration across a range of occupations and for almost every commuting zone in the US. In a nutshell, we find that labor market concentration in the average market is high, and higher concentration is associated with significantly lower posted wages. Given high concentration, mergers of employers have the potential to significantly increase *labor* market power. This type of analysis could be used by antitrust agencies to assess whether mergers can create anti-competitive effects in labor markets.

We measure labor market concentration using traditional measures such as the Herfindahl-Hirschman Index (HHI). In principle, the same analysis of concentration applies to seller and buyer power, as the horizontal merger guidelines state that "To evaluate whether a merger is likely to enhance market power on the buying side of the market, the Agencies employ essentially the framework described above for evaluating whether a merger is likely to enhance market power on the selling side of the market." The buying side of the market refers to inputs markets, including the labor market. Therefore, a merger can be said to enhance market power if it results in a high level of concentration in specific labor markets.

However, it is important to keep in mind that labor markets have particular characteristics that make them different from a typical product market. For example, even if several jobs are posted in a market, a job seeker needs to be offered the job in order to take it, while a consumer can choose which beer brand to purchase at the grocery store without this restriction. These differences between product and labor markets mean that the thresholds in the merger guidelines that were devised with a typical product market in mind may need to be modified to use in labor market applications.

To calculate market shares in geographic and occupational labor markets, we use data from CareerBuilder.com, the largest online job board in the United States, matching millions of workers and firms. We calculate vacancy shares and HHIs of market concentration for over 8,000 labor markets, defined by a combination of occupation at the SOC-6 level and commuting zone. The occupations we cover include the most frequent occupations among CareerBuilder vacancies, plus the top occupations in manufacturing and construction. We show that, on average, labor markets are highly concentrated: the average HHI is 3,157, which is the equivalent of 3.2 recruiting firms with equal shares of the total vacancy pool. An HHI of 3,157 is above the 2,500 threshold for high concentration according to the Department of Justice / Federal Trade Commission horizontal merger guidelines. Concentration varies by occupation and city, with larger cities being less concentrated.

We document a negative correlation between labor market concentration and average posted wages in that market. Labor productivity is the key confound when estimating the equilibrium relationship between wages and concentration: when concentration increases, do wages decrease because of greater exploitation or because productivity itself declined? We run both OLS and instrumental variables (IV) regressions of posted wages on concentration at the market level (HHI), using quarterly panel data ranging from 2010 to 2013. Our instrument for the IV specification is the inverse number of posting employers in other geographic markets for the same occupation in a given quarter. This instrument uses variation in market concentration that is driven by national-level changes in occupational hiring over time, and not by potentially endogenous changes in productivity within a particular local market.

The OLS and IV results are qualitatively similar, but quantitatively the instrumented estimates are much larger. In the baseline IV specification, the elasticity of the real wage with respect to the HHI is -0.127, while in the baseline OLS specification the elasticity is -0.038. Going from the 25th to the 75th level of concentration decreases posted wages by 17% in the baseline IV specification, and by 5% in the baseline OLS specifications. The instrument we use may not be fully exogenous. Therefore, we allow departures from full exogeneity (Conley, Hansen and Rossi, 2010): we find that the second-stage estimate of the impact of HHI on wages is bounded away from zero as long as the direct (endogenous) effect of the instrument on wages is not more than 75% of the reduced form effect. We thus show that the negative effect of HHI on wages is robust even for large departures from exogeneity.

One might be concerned that the impact of concentration on posted wages is endogenous due to the relationship between the number of vacancies and concentration. The sign of the bias could be positive or negative: a decrease in labor demand can lower wages and the number of firms hiring in the market, leading to higher concentration; a decrease in labor supply can increase wages, and lower the number of firms hiring, also leading to higher concentration. To alleviate this concern, we control for labor market tightness, defined as vacancies/applications, as well as for the number of vacancies itself. We find that the negative effect of concentration on wages is essentially unchanged. Overall, our results are consistent with labor market concentration creating labor market power, and hence putting downward pressure on wages.

We perform a number of additional robustness checks. Most importantly, Marinescu and Wolthoff (2016) show that posted wages are largely explained by job titles. Therefore, it is important to control for heterogeneity by job title to get an estimate of the impact of concentration on wages for a given job type. When we control for job titles, the effect of concentration on wages is still highly significant and negative but smaller, suggesting that concentration may change the composition of jobs toward lower paying jobs. We also use alternative measures of labor market concentration, such as the inverse of the number of hiring firms, or market concentration as measured by the number of applications: these alternative measures also yield a negative and highly significant impact of labor market concentration on posted wages.

This paper provides for the first time to our knowledge a measure of labor market concentration for many of the largest labor markets in the US. Our measure of concentration is distinct from the industry concentration measures used by Autor et al. (2019) and Barkai (2016): it is based on concentration in the labor market rather than concentration in the product market.[1] Our contribution is therefore complementary: while those authors show that product market concentration is associated with a lower labor share, we show that labor market concentration is associated with lower posted wages.

The papers that come closest to ours in approach are Benmelech, Bergman and Kim (2018) and Rinz (2018), which build on the present article by studying concentration of employment in labor markets defined by geography and industry, using Census data on employment by firms and establishments.

The monopsony literature in labor economics approaches the issue of market power through questions such as the impact of the minimum wage and unionization. This literature focuses on the elasticity of labor supply to the individual firm, as opposed to market concentration.[2] In such "New Monopsony" models, employers trade off wages with their employees' quit rates, and they face an upward-sloping supply curve due to search frictions, firm-specific amenities, and limited geographic mobility of workers, in addition to other mechanisms. If workers have a high labor supply elasticity, then firms pay them more to get them to stay. The literature generally finds low elasticities of labor supply and interprets this as evidence for firm-level monopsony power to reduce wages below the marginal product of labor (Webber, 2015; Dube et al., 2019).

Our approach is complementary to this literature, but with a different mechanism at play. We measure market-level concentration in local and occupational labor markets, implicitly arising from restrictions to employer entry or other characteristics of firms or industries, as

[1] To our knowledge, the last published measurement of labor market concentration is Bunting (1962). Boal and Ransom (1997) reviewed the literature.

[2] An older literature has explored the impact of labor market concentration on wages. However, this literature is mostly limited to teachers' and nurses' markets and uses cross-sectional identification, as discussed in Boal and Ransom (1997).

opposed to characteristics of workers. In our framework, firms pay higher wages if the labor market is unconcentrated and workers can expect abundant job offers from competing employers.

Buyer-side market power caused by concentration and the upward-sloping firm-level labor supply curve are mutually-reinforcing mechanisms for monopsony power and for the empirical findings from the aforementioned labor literature, such as the small effect of minimum wage increases on employment.

The remainder of the paper is organized as follows. Section 2 describes the data, and our measure of labor market concentration. Section 3 analyzes the relationship between labor market concentration and posted wages. Section 4 performs robustness tests and addresses remaining limitations. Finally, section 5 concludes.

2 Measuring labor market concentration

2.1 Data

We use proprietary data from CareerBuilder, which is the largest online job board in the United States. The site received approximately 11 million unique job seeker visits in January 2011. Job seekers can use the site for free, while firms seeking to hire workers must pay a fee of several hundred dollars to post a job opening for one month. According to CareerBuilder rules, a job posting corresponds to one vacancy, but in practice employers may sometimes hire more than one worker for a given job posting; in what follows, we refer to job postings and vacancies interchangeably. The total number of vacancies on CareerBuilder.com represents 35% of the total number of vacancies in the US in January 2011 as counted in the Job Openings and Labor Turnover Survey. The dataset used here was first used in Davis and Marinescu (2017). Occupations were selected based on counts of jobs posted between 2009 and 2012 on CareerBuilder: at the broad SOC level, i.e. SOC-5 digits, the 13 most frequent occupations were selected. We also added the three most frequent occupations in manufacturing and construction (17-2110, 47-1010, 51-1010). The full list of SOC-6 occupations can be found in Table 1: the total number is 26 because each SOC-5 may correspond to a couple of SOC-6 occupations, such as Legal Secretaries (43-6012) and Medical Secretaries (43-6013).

Our data includes, for each vacancy, the number of applicants. This allows us to calculate labor market tightness at the occupation by local labor market level as (number of vacancies)/(number of applications).

Only about 20% of the CareerBuilder vacancies post salary information. The posted wage is converted into an annual salary if it is hourly. The posted wage is defined as the middle of the range if the vacancy posts a range rather than a single value. We estimate posted wages for a given market and year-quarter as the simple average of the posted wage in the wage-posting vacancies. Figure 1 shows the distribution of log real wages across markets and year-quarters. The distribution is tri-modal. For comparison, the Figure also plots the distribution of occupational wages for the same markets from the BLS Occupational Employment Statistics. The distribution of posted wages is overall similar to the distribution of occupational wages. Posted wages have more mass in the left tail of the distribution, consistent with starting wages being lower.

2.2 Labor market definition

Given that monopsony power in labor markets has not been a focus of antitrust policy, the crucial question of how to define the relevant market for antitrust analysis is relatively unexplored in the literature. The twin imperatives contained in the Horizontal Merger Guidelines are that markets be defined in terms of "lines of commerce" and "section of the country."

Marinescu and Rathelot (2018) show that applications to a job decline rapidly with distance, although most applications are still outside the applicant's zip code. It is therefore key to define labor markets geographically to obtain meaningful measures of market concentration. For our baseline analysis, we use commuting zones (CZs) to define geographic labor markets. Commuting zones are geographic area definitions based on clusters of counties that were developed by the United States Department of Agriculture (USDA) using data from the 2000 Census on commuting patterns across counties to capture local economies and local labor markets in a way that is more economically meaningful than county boundaries. According to the USDA documentation, "commuting zones were developed without regard to a minimum population threshold and are intended to be a spatial measure of the local labor market." Marinescu and Rathelot (2018) also show that 81% of applications on CareerBuilder.com are within the commuting zone, and Manning and Petrongolo (2017) similarly find that labor market searches are local in UK data. Bartik (2018) finds evidence against full worker mobility across commuting zones. We conduct robustness checks using single counties for our geographic market definition instead of commuting zones.

When it comes to defining the analog to "line of commerce" in labor markets, the economic literature shows that there are substantial frictions associated with transitioning between jobs (Artuc, Chaudhuri and McLaren, 2010; Dix-Caneiro, 2014; Artuc and McLaren, 2015; Traiberman, 2017; Macaluso, 2017). No work, to our knowledge, attempts to define labor markets in the education space. Macaluso (2017) defines the concept of "skill remoteness" on the supply and demand sides of a labor market and finds that workers whose skills are further away from the available jobs in their local labor market (defined by city and occupation) are more likely to either move or exit the labor force in response to a layoff. Hershbein and Kahn (2016) and Modestino, Shoag and Ballance (2016) characterize the skill distribution of job vacancies as changing in response to the severity of local labor market recessions. But the extent to which workers confine their job searches to an education- or skills-delimited segment of available jobs has not yet been systematically explored (but see some evidence on search across occupations in Marinescu and Rathelot (2018)).

Using the vacancies dataset from the same source as the one used in this paper, Marinescu and Wolthoff (2016) show that, within a 6-digit SOC, the elasticity of applications to a given job posting with respect to posted wages is *negative*. Therefore, the 6-digit SOC is likely too broad to be a labor market, since we would expect applications to increase in response to posted wages in a frictional labor market (see Subsection 3.3 below). Nonetheless, we consider SOC-6 occupation to be a conservative benchmark, with the understanding that concentration measured within labor markets defined that way is likely to be an under-estimate.

We calculate labor market concentration using posted vacancies and applications to those vacancies. Concentration could also be computed using observed employment (albeit not with this dataset). The concentration of employment is almost certainly lower than the concentration of vacancies–only a subset of the firms in a given labor market (defined by geography and occupation) will be hiring at any given time. But our measure of concentration based on vacancies is more relevant for active job seekers, especially in light of evidence of lengthening job tenures, which implies that a given position will remain filled for longer (Hyatt and Spletzer, 2016). Moreover, our results about the effect of concentration on wages are estimated from variation in concentration over time within a labor market, and in our robustness checks we aggregate vacancy postings over time, which reduces observed concentration levels–toward what we would probably observe if concentration were computed from firm-level employment.

We perform our analysis at the quarterly level in the baseline specification, since the median duration of unemployment was about 10 weeks in 2016 BLS (2017). We consider for our market share calculations all vacancies or applications that occur within a given quarter, including vacancies with missing wages.

2.3 Measuring concentration

We keep an unbalanced panel of 61,017 CZ-occupation-year-quarter observations, covering the period 2010Q1-2013Q4, 681 commuting zones, and 26 SOC 6-digit occupations. These markets all include at least one vacancy with a posted wage.

Our baseline measure of market power in a labor market is the Herfindahl-Hirschman Index (HHI) calculated based on the share of vacancies of all the firms that post vacancies in that market. By confining this investigation to only the largest online job board, CareerBuilder, we add another dimension to market definition, that of the search platform. If firms post all of their jobs on CareerBuilder, we accurately measure concentration, even if firms also post their jobs on other platforms. If workers who search on CareerBuilder only use that platform, we are accurately measuring concentration for those workers. To the extent that workers search for jobs across multiple platforms *and* firms do not post all of their jobs on CareerBuilder, our data might yield an excessive concentration estimate.

The HHI is widely used as a measure of market concentration in the industrial organization literature and in antitrust practice. An advantage of this measure of market concentration is that there are guidelines for what represents a high level of market concentration. According to the DOJ/FTC guidelines: an HHI above 1500 is "moderately concentrated", and above 2500 is "highly concentrated." An HHI of 2,500 occurs when four employers have equal shares of the vacancies in a labor market. A merger that increases the HHI by more than 200 points, leading to a highly concentrated market is "presumed likely to increase market power."

While these measures and thresholds are generally used to evaluate market concentration in product markets, the antitrust agency guidelines state that "[t]o evaluate whether a merger is likely to enhance market power on the buying side of the market, the Agencies employ essentially the framework described above for evaluating whether a merger is likely to enhance market power on the selling side of the market." This implies that adverse effects of mergers on the inputs market, including the labor market, are part of the legal framework for evaluating mergers.

These DOJ/FTC HHI thresholds give some guideposts evaluate the level of concentration, but they have no precise economic meaning beyond that given to them by the historical practice of antitrust enforcement in product markets. Labor markets are different from product markets in a number of ways, and different thresholds for the labor market might make sense. For example, labor markets are two-sided: both employers and workers must agree to the employment contract, while in the product market consumers can buy without an explicit agreement by sellers. This feature of labor markets arguably makes them thinner, so reasonable HHI thresholds for the labor market might be lower than for the product market.

The formula for the HHI in market m and year-quarter t is

$$\mathrm{HHI}_{m,t} = \sum_{j=1}^{J} s_{j,m,t}^2 \tag{2.1}$$

where $s_{j,m}$ is the market share of firm j in market m. For the HHI based on vacancies, the market share of a firm in a given market and year-quarter is defined as the sum of vacancies posted in CareerBuilder by a given firm in a given market and year-quarter divided by total vacancies posted in the website in that market and year-quarter. We treat all vacancies posted by a recruiting / staffing firm as belonging to the same firm, since we cannot observe which firm the recruiting / staffing firm is hiring for.

In addition to calculating HHIs for each labor market based on shares of vacancies, we also calculated HHIs based on shares of applications (more specifically Expressions of Interest, i.e. clicking on the button "Apply now"). For the HHI based on applications, we define the market share of a firm in a given market and year-quarter as the sum of applications through the website to a given firm in a given market and year-quarter divided by the total number of applications to all firms in that market and year-quarter.

Table 2 shows summary statistics of the main variables used in our analysis. The average real wage was 41,547 USD (in 2009 dollars). The average market in our sample had 20 firms, 83 vacancies, 441,156 searches, and 3,612 applications. The average HHI based on vacancies was 3,157. The average HHI based on applications was somewhat higher: 3,480, reflecting the fact that not all vacancies received the same level of interest from job seekers.

Table 2 also shows that the average HHI calculated using shorter time periods than the quarter is higher, and the HHI using longer time periods is lower but still highly concentrated. The population-weighted quarterly HHI is lower and moderately concentrated. The population-weighted HHI is lower than the unweighted HHI because large cities tend to be less concentrated (Figure 2). The population-weighted HHI is relevant to understand the experience of the average worker, while the unweighted HHI represents the average labor market. That many labor market are highly concentrated is policy relevant because a merger review by antitrust authorities asks whether anticompetitive effects are likely in *any* one market (Marinescu and Hovenkamp, 2018).

As would be expected, county-level HHIs are higher than CZ-level HHIs, and state-level HHIs are lower than CZ-level HHIs. With the exception of a state-level definition of the labor market, all alternative definitions still show moderate to high concentration.

Figure 2 shows a map of all the commuting zones in the United States color-coded by the average HHI, based on vacancy shares. Commuting zones around large cities tend to have lower levels of labor market concentration than smaller cities or rural areas. This suggests a new explanation for the city-wage premium (Yankow, 2006; Baum-Snow and Pavan, 2012): cities, and especially large cities, tend to have less concentrated labor markets than rural areas.[3] Consistent with this interpretation, Hirsch et al. (2019) find that the urban wage premium in Germany is partly explained a higher labor supply elasticity in more densely populated city.

Figure 3 shows the distribution of the HHIs based on vacancies and of the HHI based on applications in our sample. Under both definitions for market shares, the median market is moderately concentrated, while the average market is highly concentrated.

Figure 4 shows the average HHI, based on vacancy shares, by 6-digit SOC occupation. The occupations that are least concentrated on average are "Customer service representatives", "Sales representatives, wholesale and manufacturing, technical and scientific products", and "Registered nurses", each with an average HHI of around 2,000. The occupations that are most concentrated on average are "Farm equipment mechanics", "Rail car repairers", and "Light truck or delivery services drivers", each with an average HHI well above 5,000 (which is the level of concentration of a symmetric duopsony market).

In summary, we find that reasonably defined local labor markets are highly concentrated on average. Manning (2011) notes that monopsony power is due to two types of mechanisms:

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

labor market frictions and idiosyncrasies, and collusion and institutions, with almost no evidence on the latter mechanism. High labor market concentration can facilitate collusion, so our findings start to fill in the gap on these types of mechanisms behind labor market power. A limitation of our analysis is that we only use vacancies posted on the CareerBuilder website.[4] Given that CareerBuilder is the largest job-posting website in the United States, the high level of concentration was somewhat surprising to us.

3 Concentration and wages

Figure 5 shows a binned scatter plot of the log real wage and log HHI based on vacancies. The two variables are strongly correlated and the association is close to log-linear. Figure 6 shows a similar relationship between the real wage and market concentration obtains when using the log HHI based on applications instead of the log HHI based on vacancies.

This negative correlation between market concentration and real wages is consistent with standard oligopsony theory, which predicts that firms in more concentrated labor markets should be able to pay workers wages below their marginal product. For the product market, it is well known that firms in a more concentrated market set higher prices in equilibrium (Whinston, 2007). The relationship between prices and concentration is an equilibrium one, where concentration is endogenous. Unobserved costs are the key confound when estimating the empirical relationship between prices and concentration in the product market (Whinston, 2007).

In the labor market, theory shows that the wage markdown (i.e. the gap between productivity and wages) increases with the HHI and decreases with the elasticity of labor supply (Azar, Marinescu and Steinbaum, 2019). Empirically, when we see that concentration increases and wages decrease, we cannot easily figure out if this because the markdown went up for a *given* level of productivity or because productivity itself declined. While costs are the key

[4]This is less of an issue for interpreting the within-market variation over time in concentration, which is the basis for the regression analysis in the following section.

variable confounding the relationship between concentration and prices in the product market, labor productivity is the key variable confounding the relationship between concentration and wages in the labor market.

We adopt various strategies to identify the equilibrium relationship between wages and concentration using panel regressions that control for commuting zone by occupation effects. We are thus asking how variation in concentration over time in a commuting zone by occupation pair affects wages in this same market.

3.1 Empirical specification: OLS and IV

Our baseline specification is the following:

$$\log(w_{m,t}) = \beta \cdot \log \mathrm{HHI}_{m,t} + \gamma \cdot X_{m,t} + \alpha_t + \delta_m + \varepsilon_{m,t}, \tag{3.1}$$

where $\log(w_{m,t})$ is the log real wage in market m in year-quarter t, $\log \mathrm{HHI}_{m,t}$ is the corresponding log HHI, $X_{m,t}$ is a set of controls, and α_t and δ_m are year-quarter and market (commuting zone-occupation) fixed effects and $\varepsilon_{m,t}$ is an error term.

We run a first specification with just year-quarter fixed effects. We then add successively market (CZ by SOC-6) fixed effects and log tightness (defined as the number of vacancies divided by the number of applications in a labor market) in the commuting zone and occupation for a given year-quarter. We then run a fourth specification further controlling for year-quarter by commuting zone, and finally we also add year-quarter by SOC fixed effects in a fifth specification, to control for *any* possible changes in the characteristics of the commuting zone or the occupation over time. In a robustness test, we also control for the number of vacancies in the market, which can be interpreted as a measure of labor demand independent of the level of concentration. We cluster standard errors at the commuting zone-occupation level.

The key threat to identification is that there is a time-varying market-specific variable that is correlated with HHI and drives wages. The key confound according to the oligopsony theory discussed above is labor productivity. What other confounds are most likely? According to search and matching theory, posted wages are determined by labor market tightness, productivity, and the worker's out-of-work benefit (Rogerson, Shimer and Wright, 2005). We already control for labor market tightness. Since unemployment benefits are determined at the state level, we are able to control for workers' out-of-work benefits by controlling for market fixed effects, and, in some specifications, market-by-time fixed effects. Therefore, the main threat to identification remains time-varying market-specific productivity changes.

To further address the issue of the endogeneity of HHI, we instrument the HHI with the average of $\log(1/N)$ in other commuting zones for the same occupation and time period (where N refers to the number of firms in the market). That is, for each commuting zone-occupation-time period combination, we calculate the average of $\log(1/N)$ for the same occupation for every other commuting zone. We use $\log(1/N)$ instead of HHI as the instrument because it is less likely to be endogenous, as it does not depend on market shares. This instrument provides us with variation in market concentration that is driven by national-level changes in the occupation, and not by changes in the occupation in that particular local market. In particular, the instrument should be independent of the occupational productivity in the local labor market, which is likely to be the main confounding factor in the baseline OLS regressions. For example, if the productivity of customer service representatives falls in the Chicago area, this could both decrease wages and increase concentration, since fewer firms would likely be recruiting. By instrumenting with the number of firms posting vacancies for customer service representatives in other areas, we rule out a direct effect of productivity in Chicago on the HHI.

This type of instrumental variables strategy is commonly used in industrial organization to address the endogeneity of prices in a local product market. For example, Nevo (2001) uses prices in other geographic markets to instrument for city-level prices of various products in the ready-to-eat cereal industry.

The main threat to identification for the instrumental variable strategy is that productivity shocks could be correlated across areas. For example, a national level decline in the productivity of customer service representatives would likely increase concentration and decrease wages in most labor markets. Therefore, the instrument protects us against a spurious correlation between concentration and outcomes that is due to local changes in productivity, but not against national-level changes in productivity (for an occupation relative to other occupations) that influence both concentration and other labor market outcomes.

The instrument may not be not fully exogenous in the sense that it may have a direct effect on wages that does not go through local concentration. However, it is plausibly more exogenous that the local market HHI, in particular because it is less likely to be correlated with uncontrolled-for variations in local productivity. We exploit this idea by deriving bounds for the causal effect of HHI on wages using the method developed by Conley, Hansen and Rossi (2010). Suppose that the instrument is not fully exogenous in the sense that it has a direct effect on posted wages, with a coefficient of $\gamma \neq 0$. If we assume a range of values for γ between 0 (perfectly exogenous) and the reduced form effect, we can derive an interval for the causal effect of the HHI on wages that takes into account deviations from exogeneity ($\gamma \neq 0$). This procedure allows us to determine how big the direct effect of the instrument on wages could be for the interval of the causal effect of HHI on wages to exclude zero.

3.2 Regression results

We find that higher labor market concentration is associated with significantly lower real wages. Table 4 Panel A shows the results from the baseline wage regressions. In the first regression, using vacancy-share HHIs and only year-quarter fixed effects, we find that a one log point increase in the HHI is associated with a decline in wages of about 0.103 log points. Further controlling for market fixed effects (CZ by 6-digit SOC) reduces the coefficient to -.0347, showing that some of the negative relationship between posted wages and HHI is driven by cross-sectional variation in posted wages. Specification (3) shows that controlling for log tightness does not substantially change the result from specification (2). We consider specification (3) to be the baseline for OLS results. Figure 7 shows a binned scatterplot corresponding to specification (3): the relationship between the residualized wages and the residualized HHI is negative and linear, similar to the raw relationship between wages and HHI (Figure 5).

Specifications 4 and 5 allow for commuting zone and occupation effects to change over time. Adding year-quarter by CZ fixed effects does not affect the impact of HHI on wages (compare column 3 and 4 in Table 4), showing that the effects are not driven by time-varying effects at the CZ level. When we further add year-quarter by 6-digit SOC fixed effects (column 5), the impact of HHI on wages remains negative and of a similar size. This shows that the negative impact of HHI on wages is not explained away by changes in occupational wages over time, due to e.g. technological change.

Specifications (6) to (8) show analogous results but based on the instrumental variables estimation strategy (see Table 3 for the first stage). The estimated effect is still negative but much larger in absolute value. The IV estimate may be higher because it corrects the endogeneity bias from market-level labor supply and demand effects, and possibly also corrects for measurement error. A one log point increase in the HHI is associated with a decline in wages of about 0.14 log points. This implies that an increase in HHI of 200 in a market with an HHI of 2000 (moderately concentrated), which is an increase of 10 log points, is associated with a decline in wages of about 1.4%. Going from the 25th percentile of market concentration to the 75th percentile of market concentration is associated with a decline in wages of 5% using specification (3), and of 17% using specification (7), our baseline specification for the IV.[5]

The main threat to identification for the instrumental variable strategy is that productivity shocks to occupations could be correlated across areas. We cannot control for occupation by time fixed effects in the IV specifications due to the fact that the instrument is essentially defined at that level. Nevertheless, it is reassuring to see that controlling for occupation by time effects does not substantively change the OLS results (column 4).

We recognize that the instrument may not be not fully exogenous, and we provide bounds

[5]Going from the 25th to the 75th percentiles of the residualized log HHI (after market and CZ-year-quarter fixed effects) decreases wages by 2% using specification (3) and 6% using specification (7).

on the second stage effect of HHI on wages, assuming a degree of endogeneity in the instrument. Using market-level data, we regress wages on the instrument and controls (Table 5), which gives us the reduced form effect of the instrument. We then calculate the bounds for the second stage effect of HHI on wages, assuming that the direct effect of the instrument on wages (γ) ranges from zero (perfectly exogenous) to the reduced form effect. We use Stata's plausexog and start with a simple specification in column 1, and control for tightness in column 2. When controlling for tightness, the second stage effect of HHI on wages ranges between -0.177 and 0.036 (Table 5 , col. 2, β bounds). The bounds for the second stage estimate exclude zero as long as the direct effect of the instrument is smaller than -0.112 (γ_{max} in Table 5 , col. 2), or 75% of the reduced form effect. Specification 3 adds year-quarter by CZ fixed effects, and the results are very similar to specification 2. We conclude that the negative impact of concentration on wages is robust to a large degree of instrument endogeneity: the instrument would have to be very endogenous for the impact of concentration on wages to plausibly take positive values.

3.3 Controlling for job titles

Marinescu and Wolthoff (2016) showed that job titles are an important predictor of wages and are informative about the type of job and required skills beyond a pure wage-signalling effect. We are thus interested in studying to what extent market concentration affects wages through job titles and to what extent it has a direct effect beyond the effect that can be explained by job titles. For this purpose, we conducted regressions at the individual vacancy level controlling for job title fixed effects (based on strings capturing the first three words in the vacancy's job title).

The results are shown in Table 4 Panel B. The first three specifications show results using the same controls as in the market-level baseline regressions, and find similar results. The fourth specification controls for commuting-zone times job-title fixed effects. The effect has a negative sign and is statistically significant, but the magnitude is about half of the effect without job title fixed effects. This mitigation of the effect is present in both the OLS and the IV specifications.

This indicates that the effect of an increase in market concentration on wages is expressed both directly through lower wages conditional on a job title, as well as by increasing the likelihood of posting lower-wage job titles.

4 Robustness checks

4.1 Interaction with city size

We tested whether the negative effect of market concentration on wages is driven by small or large cities, or whether it holds across the whole range of city sizes in our sample. For this purpose, we ran a specification interacting the vacancy HHI in a market with a 5th-order polynomial in the percentile of the population of that market's commuting zone, which we instrument using a 5th-order polynomial in the mean of log(1/N) for the same occupation in other CZs.

The estimated effect of market concentration as a function of commuting zone population percentile is shown in Figure 8, together with 95% confidence bands. The effect is negative and significant over the range of population going from the 10th to the 90th percentile, and it it is higher (in absolute value) for smaller markets than larger markets.

Therefore, less populated commuting zones are not only more concentrated on average, but an increase in concentration has a more negative effect on wages.

4.2 Controlling for the number of vacancies

A key threat to identification is that wages are affected by local demand. We can use the number of posted vacancies as a proxy for local demand. The negative effect of HHI on posted wages remains of the same magnitude in both OLS and IV when controlling for the log of the number of vacancies posted (Table 6, col. 1 and 2).

4.3 Excluding monopsony (HHI=1) markets

The histogram in Figure 3 shows that many markets in the sample only have one firm hiring. We checked that our estimates are not sensitive to excluding these markets by running additional regressions that do exactly that. The results from the panel IV specification are reported in Table 6, specification (3) and (4), which show that the magnitude and significance of the estimated effect is similar to the analogous specification in the baseline in both OLS and IV.

4.4 Alternative market definitions

We chose SOC-6 as the definition of a market in terms of occupation. Broadening the definition of the labor market to SOC-2 by CZ instead of SOC-6 by CZ makes the effect of HHI on wages larger in both OLS and IV (Table 6, col. 5 and 6). On the other hand, narrowing the definition of the labor market to a job title by commuting zone makes the estimated effect of HHI on posted wages smaller (Table 6, col. 7), and the effect becomes insignificant in IV (Table 6, col.8). One possible explanation for this pattern of results is measurement error: a broader market definition entails more vacancies that the HHI can be calculated from, thereby reducing measurement error.

In terms of geography, we chose to use commuting zones as a market definition because they were designed to capture meaningful geographic labor markets based on commuting patterns across counties. However, the correct geographic definition for labor market competition for hiring is still an open question. We decided to test the sensitivity of our results by using an alternative definition based on counties, and running panel IV specifications analogous to our baseline.

The results are shown in Table 7, specification (3). The estimated coefficient is similar to those in the baseline, indicating that our results are robust to other plausible geographic labor market definitions.

4.5 Alternative concentration measures

As a robustness check, we estimated panel IV regressions similar to our baseline specification from Table 4, column 6, but using log 1/N as the measure of market concentration. The results are similar to the baseline, and shown in Table 7, specification (1).

We also estimated regressions using log HHI based on share of applications as the measure of concentration, again with similar results. The results are in Table 7, specification (2). This shows that our results are robust to using a range of standard measures of market concentration, and therefore not driven by a particular choice of measure.

4.6 Cross-sectional specification

Our baseline specification identifies the effect of market concentration on wages purely from variation within a market over time. One may also be interested in identification from cross-sectional variation. We implemented a specification based on the entire 2010-2013 period. We included CZ fixed effects and 6-digit SOC fixed effects, so that our estimates are not driven by variation in average wages across cities, or in average wages across occupations. Similar to the baseline, we instrument the log HHI using the log 1/N, except that we use the number of firms for the entire period. The impact of concentration on posted wages is still negative and significant in this cross-sectional data (Table 7, specification (4)). Furthermore, we find that the impact of concentration on prevailing wages measured from the BLS occupational employment statistics is also negative and significant (specification (5)). Figure 9 plots the negative relationship between residualized HHI and wages in these IV regressions (panels C and D). For comparison, in panels A and B, the figure also shows the relationship between residualized HHI and wages in OLS, which is less steep than in IV.

The estimated impact of HHI on occupational wages is smaller than on posted wages, presumably because the market concentration among vacancies has a more direct effect on posted wages than on the wages of incumbent workers. Indeed, the wages of stayers – which are included in the BLS occupational wage – are less sensitive to economic conditions than the wages of new hires (Carneiro, Guimarães and Portugal, 2012; Haefke, Sonntag and van Rens, 2013). Overall, these results alleviate the concern that our results are driven by the less than fully representative nature of our data.

4.7 Controlling for fraction of vacancies posting wages

An important limitation of the dataset is that only a fraction of the vacancies on CareerBuilder post wages. At the market level, it may be that wage posting is correlated with an omitted variable that determines both wages and concentration. This could bias the estimated coefficient on concentration in the wage regression. To assess the potential for such a bias, we run a panel IV specification controlling for the fraction of vacancies in each market that post wages. Table 7, specification (6) shows the results. We find that this variable has a positive effect on wages, but does not meaningfully affect the coefficient on log HHI.

4.8 Controlling for tightness based on searches instead of applications

Another concern is that the tightness measure could be endogenous with respect to wages: high-wage vacancies get more applications, so this lowers the tightness measure. As an alternative measure of tightness, we use the log of the ratio of total vacancies in the market to total searches in the market. Searches should not be affected by posted wages because workers do not search by wage by typically by job title and location, so this can address the endogeneity concern. Table 7, specification (7) shows the results from the corresponding panel IV specification, which are similar to those in the baseline specification.

4.9 Remaining limitations

Our analysis accounts for a number of biases in the estimation of the relationship between labor market concentration and posted wages. However, a number of limitations remain.

Only 20% of vacancies post wages, and we are therefore not measuring all wages in a given occupation by commuting zone market. However, Marinescu and Wolthoff (2016) show that the distribution of posted wages on CareerBuilder is very similar to the distribution of wages for employed workers in the Current Population Survey. Therefore, posted wages are typical of wages overall in the labor market.

Our data comes from a single website, CareerBuilder.com. While this is the largest US job search website, and contains overall about a third of US vacancies, it does not contain all vacancies in the occupations that are in our sample. This could lead us to overestimate labor market concentration for the selected occupations. At the same time, smaller occupations that were not included in our sample will typically be even more concentrated, which results in a higher average concentration when a broader sample of occupations is used (Azar et al., 2018). Furthermore, the fact that we only capture some of the vacancies should not affect our estimate of the relationship between posted wages and labor market concentration.

Our data contains the most frequent occupations by number of vacancies on CareerBuilder.com, and a number of manufacturing occupations. Therefore, our results, while fairly general, do not necessarily apply to the whole US labor market. It is noteworthy that Benmelech, Bergman and Kim (2018) and Rinz (2018) find a negative and significant relationship between wages and employment concentration at the county and industry level. Therefore, studying employment rather than vacancies and changing the labor market definition does not affect the basic fact that wages are negatively associated with labor market concentration.

5 Discussion and conclusion

Labor economists are increasingly questioning the assumption of almost-perfectly-competitive labor markets (Card et al., 2016), and they have begun to address the antitrust policy implications of relaxing that assumption. Ashenfelter and Krueger (2017) study the prevalence of anti-competitive no-poaching language in franchising contracts, leading to a series of recent antitrust cases against franchise employers. Marinescu and Hovenkamp (2018) and Naidu, Posner and Weyl (2018) both consider the implications of concentrated labor markets for merger enforcement. On the heels of this flurry of academic papers, the chairman of the Federal Trade Commission said in Congressional testimony that he had instructed the agency's staff to examine the labor market impact of every merger the agency reviews, and he further elaborated that market definition in labor markets for antitrust enforcement purposes should be guided by the elasticity of labor supply to the individual firm (Simons, 2018).

The idea that monopsony power can harm efficiency dates to the origins of American antitrust policy. One of the reasons Senator John Sherman gave for legislating against monopoly was that it has the power to fix wages due to a lack of competition: "[i]t commands the price of labor without fear of strikes, for in its field it allows no competitors." (Congressional Record 2457, 1890). The horizontal merger guidelines recognize that the same framework can be applied to market power on the part of buyers as well as sellers, although there have been few merger challenges premised on monopsony theories of harm, and none in which the labor market is where the monopsony power is being challenged.[6]

In this paper, we contribute to this growing debate by calculating measures of market concentration in local labor markets for the most frequent occupations on the leading employment website CareerBuilder.com. We have shown that concentration is high, and increasing concentration is associated with lower wages. Our results suggest that the anti-competitive effects of concentration on the labor market could be important. The type of analysis we provide could be used to incorporate labor market concentration concerns as a factor in antitrust analysis.

[6]Antitrust agencies have recently brought to court conduct cases regarding labor market monopsony in which they found evidence of overt written agreements not to compete for workers (DOJ, 2007, 2010).

References

Artuc, Erhan, and John McLaren. 2015. "Trade policy and wage inequality: A structural analysis with occupational and sectoral mobility." *Journal of International Economics*, 97: 28–41.

Artuc, Erhan, Shubham Chaudhuri, and John McLaren. 2010. "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." *American Economic Review*, 100: 1008–1045.

Ashenfelter, Orley, and Alan B. Krueger. 2017. "Theory and Evidence on Employer Collusion in the Franchise Sector." Princeton University Industrial Relations Section Working Paper. DOI: 10.3386/w23396.

Ashenfelter, Orley C., Henry Farber, and Michael R. Ransom. 2010. "Labor market monopsony." *Journal of Labor Economics*, 28(2): 203–210.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2019. "The Fall of the Labor Share and the Rise of Superstar Firms." *Quarterly Journal of Economics*.

Azar, José A, Ioana Marinescu, Marshall I Steinbaum, and Bledi Taska. 2018. "Concentration in US Labor Markets: Evidence From Online Vacancy Data." National Bureau of Economic Research Working Paper 24395.

Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2019. "Measuring Labor Market Power Two Ways." *American Economic Association Papers & Proceedings*, 109: 317–21.

Barkai, Simcha. 2016. "Declining Labor and Capital Shares."

Bartik, Alexander W. 2018. "Moving Costs and Worker Adjustment to Changes in Labor Demand: Evidence from Longitudinal Census Data."

Baum-Snow, Nathaniel, and Ronni Pavan. 2012. "Understanding the City Size Wage Gap." *The Review of Economic Studies*, 79(1): 88–127.

Benmelech, Efraim, Nittai Bergman, and Hyunseob Kim. 2018. "Strong Employers and Weak Employees: How Does Employer Concentration Affect Wages?"

BLS. 2017. "Unemployed persons by duration of unemployment." Bureau of Labor Statistics.

Boal, William M., and Michael R Ransom. 1997. "Monopsony in the Labor Market." *Journal of Economic Literature*, 35(1): 86–112.

Bunting, Robert. 1962. *Employer Concentration in Local Labor Markets.* University of North Carolina Press.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline. 2016. "Firms and Labor Market Inequality: Evidence and Some Theory."

Carneiro, Anabela, Paulo Guimarães, and Pedro Portugal. 2012. "Real Wages and the Business Cycle: Accounting for Worker, Firm, and Job Title Heterogeneity." *American Economic Journal: Macroeconomics*, 4(2): 133–152.

CEA. 2016. "Labor market monopsony: trends, consequences, and policy responses." White House Council of Economics Adivsors.

Clarke, Damian. 2017. "PLAUSEXOG: Stata module to implement Conley et al's plausibly exogenous bounds."

Conley, Timothy G., Christian B. Hansen, and Peter E. Rossi. 2010. "Plausibly Exogenous." *The Review of Economics and Statistics*, 94(1): 260–272.

Davis, Steven J., and Ioana E. Marinescu. 2017. "Posted wages and labor market conditions." working paper.

De Loecker, Jan, and Jan Eeckhout. 2017. "The Rise of Market Power and the Macroeconomic Implications."

Dix-Caneiro, Rafael. 2014. "Trade Liberalization and Labor Market Dynamics." *Econometrica*, 82: 825–885.

DOJ. 2007. "United States v. Arizona Hospital and Healthcare Association." *Complaint*.

DOJ. 2010. "United States v. Adobe Systems, Inc. et al." *Complaint*.

Dube, Arindrajit, Jeff Jacobs, Suresh Naidu, and Siddharth Suri. 2019. "Monopsony in Online Labor Markets." *American Economic Review: Insights*.

Falch, Torberg. 2010. "The Elasticity of Labor Supply at the Establishment Level." *Journal of Labor Economics*, 28(2): 237–266.

Haefke, Christian, Marcus Sonntag, and Thijs van Rens. 2013. "Wage rigidity and job creation." *Journal of Monetary Economics*, 60(8): 887–899.

Hershbein, Brad, and Lisa B. Kahn. 2016. "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings." National Bureau of Economic Research Working Paper 22762. DOI: 10.3386/w22762.

Hirsch, Boris, Elke J. Jahn, Alan Manning, and Michael Oberfichtner. 2019. "The Urban Wage Premium in Imperfect Labour Markets." Centre for Economic Performance, LSE dp1608.

Hyatt, Henry R., and James R. Spletzer. 2016. "The Shifting Job Tenure Distribution." *Labour Economics*, 41: 363–377.

Macaluso, Claudia. 2017. "Skill remoteness and post-layoff labor market outcomes."

Manning, Alan. 2010. "The plant size-place effect: agglomeration and monopsony in labour markets." *Journal of Economic Geography*, 10(5): 717–744.

Manning, Alan. 2011. "Imperfect competition in the labor market." *Handbook of labor economics*, 4: 973–1041.

Manning, Alan, and Barbara Petrongolo. 2017. "How Local Are Labor Markets? Evidence from a Spatial Job Search Model." *American Economic Review*, 107(10): 2877–2907.

Marinescu, Ioana, and Herbert J. Hovenkamp. 2018. "Anticompetitive Mergers in Labor Markets." *Faculty Scholarship at Penn Law*.

Marinescu, Ioana, and Roland Rathelot. 2018. "Mismatch Unemployment and the Geography of Job Search." *American Economic Journal: Macroeconomics*, 10(3): 42–70.

Marinescu, Ioana, and Ronald Wolthoff. 2016. "Opening the Black Box of the Matching Function: the Power of Words." National Bureau of Economic Research Working Paper 22508. DOI: 10.3386/w22508.

Matsudaira, Jordan D. 2013. "Monopsony in the Low-Wage Labor Market? Evidence from Minimum Nurse Staffing Regulations." *The Review of Economics and Statistics*, 96(1): 92–102.

Modestino, Alicia Sasser, Daniel Shoag, and Joshua Ballance. 2016. "Downskilling: Changes in Employer Skill Requirements Over the Business Cycle."

Naidu, Suresh, Eric A. Posner, and E. Glen Weyl. 2018. "Antritrust Remedies for Labor Market Power." *Harvard Law Review*.

Nevo, Aviv. 2001. "Measuring market power in the ready-to-eat cereal industry." *Econometrica*, 69(2): 307–342.

Ransom, Michael R, and David P. Sims. 2010. "Estimating the Firm's Labor Supply Curve in a "New Monopsony" Framework: Schoolteachers in Missouri." *Journal of Labor Economics*, 28(2): 331–355.

Rinz, Kevin. 2018. "Labor Market Concentration, Earnings Inequality, and Earnings Mobility." Center for Economic Studies, US Census Bureau Working Paper 2018-10.

Rogerson, Richard, Robert Shimer, and Randall Wright. 2005. "Search-Theoretic Models of the Labor Market: A Survey." *Journal of Economic Literature*, 43(4): 959–988. ArticleType: research-article / Full publication date: Dec., 2005 / Copyright © 2005 American Economic Association.

Simons, Joseph. 2018. "Oversight of the Enforcement of the Antitrust Laws." Senate Judiciary Committee Congressional Hearing.

Staiger, Douglas O, Joanne Spetz, and Ciaran S Phibbs. 2010. "Is there monopsony in the labor market? Evidence from a natural experiment." *Journal of Labor Economics*, 28(2): 211–236.

Traiberman, Sharon. 2017. "Occupations and Import Competition: Evidence from Denmark."

Webber, Douglas A. 2015. "Firm market power and the earnings distribution." *Labour Economics*, 35: 123–134.

Whinston, Michael D. 2007. "Chapter 36 Antitrust Policy toward Horizontal Mergers." In *Handbook of Industrial Organization*. Vol. 3, 2369–2440. Elsevier.

Yankow, Jeffrey J. 2006. "Why do cities pay more? An empirical examination of some competing theories of the urban wage premium." *Journal of Urban Economics*, 60(2): 139–161.

Table 1. List of occupations. This table shows the 6-digit SOC occupations present in our sample.

SOC code	Occupation description
11-3011	Administrative services managers
13-2011	Accountants and Auditors
13-2051	Financial Analysts
13-2052	Personal financial advisers
13-2053	Insurance Underwriters
13-2061	Financial Examiners
15-1041	Computer support specialists
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors
17-2112	Industrial engineers
29-1111	Registered nurses
41-4011	Sales representatives, wholesale & manufacturing, technical & scientific products
41-9041	Telemarketers
43-3031	Bookkeeping, accounting, and auditing clerks
43-4051	Customer service representatives
43-6011	Executive secretaries and administrative assistants
43-6012	Legal Secretaries
43-6013	Medical secretaries
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
47-1011	First-Line Supervisors of Construction Trades and Extraction Workers
49-3041	Farm equipment mechanics
49-3042	Mobile Heavy Equipment Mechanics, Except Engines
49-3043	Rail Car Repairers
51-1011	First-line supervisors/managers of production and operating workers
53-3031	Driver/sales workers
53-3032	Truck drivers, heavy and tractor-trailer
53-3033	Light Truck or Delivery Services Drivers

Table 2. Summary statistics. This table shows summary statistics for our sample consisting of commuting zone-occupational code (6-digit SOC) labor markets over the period 2010Q1–2013Q4.

	Mean	Std. Dev.	Min	Max	Obs.
Real Wage	41547.36	36216.76	4.71	5504385	61017
Vacancies	82.95	224.39	1	17928	61017
Applications	3612.96	14416.02	0	528289	61017
Searches	441156.09	1385720.05	0	78808601	61017
Log Tightness	-2.9	1.36	-7.64	4.48	60200
Number of Firms	20.03	35.78	1	571	61017
HHI (Vacancies, CZ Quarterly) - Baseline	3157.02	2923.92	66.04	10000	61017
HHI (Applications, CZ Quarterly)	3480.17	3061.03	0	10000	61017
HHI (Vacancies, CZ Monthly)	3251.69	3004.4	74.23	10000	132461
HHI (Vacancies, CZ Semesterly)	3090.29	2872.86	58.57	10000	38503
HHI (Vacancies, CZ Yearly)	2970.47	2780.11	51.91	10000	24060
HHI (Vacancies, CZ Whole Period)	2541.6	2498.51	54.76	10000	8979
HHI (Applications, CZ Monthly)	3790.37	3132.18	0	10000	132461
HHI (Applications, CZ Semesterly)	3315.38	3017.08	0	10000	38503
HHI (Applications, CZ Yearly)	3120	2900.47	0	10000	24060
HHI (Applications, CZ Whole Period)	2722.97	2653.19	0	10000	8979
HHI (Vacancies, CZ Quarterly, Population-Weighted)	1690.74	1942.09	66.04	10000	61013
HHI (Applications, CZ Quarterly, Population-Weighted)	1848.51	2127.09	0	10000	61013
HHI (Vacancies, County Quarterly)	4222.52	3331.36	76.09	10000	111109
HHI (Applications, County Quarterly)	4563.85	3369.67	0	10000	111109
HHI (Vacancies, State Quarterly)	1358.48	1634.58	64.01	10000	15124
HHI (Applications, State Quarterly)	1458.09	1781.24	0	10000	15124

Table 3. Effect of Market Concentration on Real Wages: Panel Regressions (First Stage).
Data are for the period 2010Q1-2013Q4. We cluster standard errors at the market level.

Panel A: Market-level regressions

	Dependent Variable: Log HHI (Vacancies)		
	(1)	(2)	(3)
Average Log (1/N) in Other Markets	1.005***	1.046***	1.074***
	(0.0344)	(0.0323)	(0.0340)
Log Tightness		0.171***	0.198***
		(0.00471)	(0.00558)
Market (CZ × 6-digit SOC) FE	✓	✓	✓
Year-quarter FE	✓	✓	
Year-quarter FE × CZ FE			✓
Observations	59,485	58,642	56,679
R-squared	0.846	0.852	0.865

Panel B: Vacancy-level regressions

	Dependent Variable: Log HHI (Vacancies)			
	(1)	(2)	(3)	(4)
Average Log (1/N) in Other Markets	0.871***	0.926***	0.889***	0.931***
	(0.129)	(0.124)	(0.116)	(0.0760)
Log Tightness				0.341***
			0.451***	0.252***
		(0.0162)	(0.0186)	(0.0146)
CZ × 6-digit SOC FE	✓	✓	✓	
Year-quarter FE	✓	✓		✓
Year-quarter FE × CZ FE			✓	
CZ × Job-Title FE				✓
Observations	1,023,295	1,021,185	1,020,510	955,641
R-squared	0.902	0.913	0.928	0.948

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Effect of Market Concentration on Real Wages: Panel Regressions.
Data are for the period 2010Q1-2013Q4. We cluster standard errors at the market level.

Panel A: Market-level regressions

	Dependent Variable: Log(Real Wage)							
	OLS					IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log HHI (Vacancies)	-0.103***	-0.0347***	-0.0399***	-0.0378***	-0.0300***	-0.141***	-0.143***	-0.127***
	(0.00456)	(0.00377)	(0.00392)	(0.00406)	(0.00422)	(0.0191)	(0.0181)	(0.0176)
Log Tightness			0.0113***	0.0132***	0.00686*		0.0283***	0.0305***
			(0.00320)	(0.00357)	(0.00360)		(0.00427)	(0.00479)
Year-quarter FE	✓	✓	✓			✓	✓	
Market (CZ × 6-digit SOC) FE		✓	✓	✓	✓	✓	✓	✓
Year-quarter FE × CZ FE				✓	✓			✓
Year-quarter FE × 6-digit SOC FE					✓			
Observations	61,017	59,485	58,642	56,679	56,677	59,485	58,642	56,679
R-squared	0.042	0.674	0.672	0.715	0.738	-0.018	-0.015	-0.012
Kleibergen-Paap F-stat						854.3	1051	996.7

Panel B: Vacancy-level regressions

	Dependent Variable: Log(Real Wage)							
	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log HHI (Vacancies)	-0.0327***	-0.0331***	-0.0314***	-0.0154***	-0.200***	-0.192***	-0.188***	-0.116***
	(0.00453)	(0.00476)	(0.00500)	(0.00377)	(0.0398)	(0.0361)	(0.0370)	(0.0184)
Log Tightness		0.000665	0.00429	0.00818***		0.0540***	0.0737***	0.0315***
		(0.00342)	(0.00462)	(0.00297)		(0.0133)	(0.0180)	(0.00601)
CZ × 6-digit SOC FE	✓	✓	✓		✓	✓	✓	
Year-quarter FE	✓	✓		✓	✓	✓		✓
Year-quarter FE × CZ FE			✓				✓	
CZ × Job-Title FE				✓				✓
Observations	1,023,295	1,021,185	1,020,510	955,641	1,023,295	1,021,185	1,020,510	955,641
R-squared	0.533	0.533	0.541	0.849	0.522	0.524	0.534	0.847
Kleibergen-Paap F-stat					45.62	56.18	58.72	150.1

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Plausibly Exogenous Instrument Regressions (Market-level data).
Data are for the period 2010Q1-2013Q4. We consider the following model, in which the instrument is not fully exogenous and therefore can enter in the second stage:

$$\log(w_{m,t}) = \beta \cdot \log \mathrm{HHI}_{m,t} + \gamma \cdot z + \theta \cdot X_{m,t} + \alpha_t + \delta_m + \varepsilon_{m,t},$$

where z is our instrumental variable. We implement the plausibly exogenous instrument regression methodology as follows. We start by running reduced form OLS regressions analogous to our IV specifications, but including the instrument directly in the second stage instead of log HHI. The value of $\hat{\gamma}$ in the table refers to the coefficient of the instrument in this regression. We take $\hat{\gamma}$ as the lower bound for the range of γ, and zero as the upper bound, and then compute bounds for the coefficient on log HHI (β) using the plausibly exogenous regression methodology of Conley, Hansen and Rossi (2010). We implement the methodology by (i) within-transforming all the variables (including the dependent variable, the regressors, and the instruments) by running regressions with each variable on the left hand side and the corresponding set of fixed effects on the right hand side, and taking the residuals as the transformed variables, and (ii) running the plausibly exogenous instrument regressions on the within-transformed variables using the plausexog command in Stata developed by Clarke (2017). We cluster standard errors at the market level. We also calculate the value of the lower bound for γ that would make the interval for β be fully to the left of zero. We call this value γ_{max}.

	Dependent Variable: Log(Real Wage)		
	(1)	(2)	(3)
$\hat{\gamma}$	-0.141***	-0.149***	-0.137***
	(0.0186)	(0.0184)	(0.0184)
Log Tightness		0.00387	0.00526
		(0.00310)	(0.00344)
Market (CZ × 6-digit SOC) FE	✓	✓	✓
Year-quarter FE	✓	✓	
Year-quarter FE × CZ FE			✓
Observations	59,485	58,642	56,679
R-squared	0.674	0.671	0.715
β (Lower Bound)	-0.178	-0.177	-0.157
β (Upper Bound)	0.0362	0.0357	0.0349
γ_{max}	-.105	-.112	-.100

*** p<0.01, ** p<0.05, * p<0.1

Table 6. Effect of Market Concentration on Real Wages: Robustness Checks 1.

Data are for the period 2010Q1-2013Q4. We cluster standard errors at the market level. In IV specifications, we use as instrument the average of log(1/N) for the same 6-digit SOC occupation in other commuting zones.

	Dependent Variable: Log(Real Wage)							
	Control for vacancies		Excluding HHI=1		SOC-2		Job titles	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log HHI (Vacancies)	-0.0373***	-0.150***	-0.0377***	-0.131***	-0.0491***	-0.303***	-0.00644***	0.0337
	(0.00405)	(0.0217)	(0.00425)	(0.0185)	(0.00522)	(0.0296)	(0.00247)	(0.0350)
Log Tightness	0.0127***	0.0378***	0.0135***	0.0359***	0.0181***	0.0683***	-0.00673***	-0.0102***
	(0.00374)	(0.00604)	(0.00424)	(0.00582)	(0.00504)	(0.00765)	(0.000772)	(0.00237)
Log Vacancies	0.00208	-0.0143***	0.00467					
	(0.00331)	(0.00459)	(0.00363)					
CZ FE × 6-digit SOC FE	✓	✓	✓	✓	✓	✓		
Year-quarter FE × CZ FE	✓	✓	✓	✓	✓	✓	✓	✓
CZ × Job-Title FE							✓	✓
Observations	56,679	56,679	51,607	51,607	36,023	36,023	231,072	182,354
R-squared	0.715	0.709	0.709	0.705	0.675	-0.101	0.879	-0.002
Kleibergen-Paap F-stat		565.6		907.1		667.3		462.8

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Effect of Market Concentration on Real Wages: Robustness Checks 2 (Panel IV).
Data are for the period 2010Q1-2013Q4. We cluster standard errors at the market level. In all cases, we report results from a panel IV specification using the average of log(1/N) for the same 6-digit SOC occupation in other commuting zones.

	Dependent Variable: Log(Real Wage)						
	$1/N$	HHI (EOI)	County	Cross-Section	Cross-Section (BLS Wages)	Fraction Posting Wage	Search Tightness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (1/N)	-0.0882***						
	(0.0123)						
Log HHI (EOI)		-0.102***					
		(0.0142)					
Log HHI (Vacancies)			-0.142***	-0.0927***	-0.0352***	-0.157***	-0.125***
			(0.0153)	(0.0156)	(0.00555)	(0.0231)	(0.0185)
Log Tightness	0.00898***	0.00301	0.0248***	0.0300***	0.00308	0.0325***	
	(0.00345)	(0.00350)	(0.00337)	(0.00997)	(0.00349)	(0.00510)	
Fraction Posting Wage						0.147***	
						(0.0305)	
Log (Vacancies/Searches)							0.0252***
							(0.00447)
CZ FE × 6-digit SOC FE	✓	✓				✓	✓
Year-quarter FE × CZ FE	✓	✓				✓	✓
County FE × 6-digit SOC FE			✓				
Year-quarter FE × County FE			✓				
CZ FE				✓	✓		
6-digit SOC FE				✓	✓		
Observations	56,679	56,679	94,714	8,895	6,228	56,679	57,383
R-squared	0.714	0.711	0.722	0.606	0.937	0.709	0.712
Kleibergen-Paap F-stat	2008	1973	1473	1546	1494	643	800.8

*** p<0.01, ** p<0.05, * p<0.1

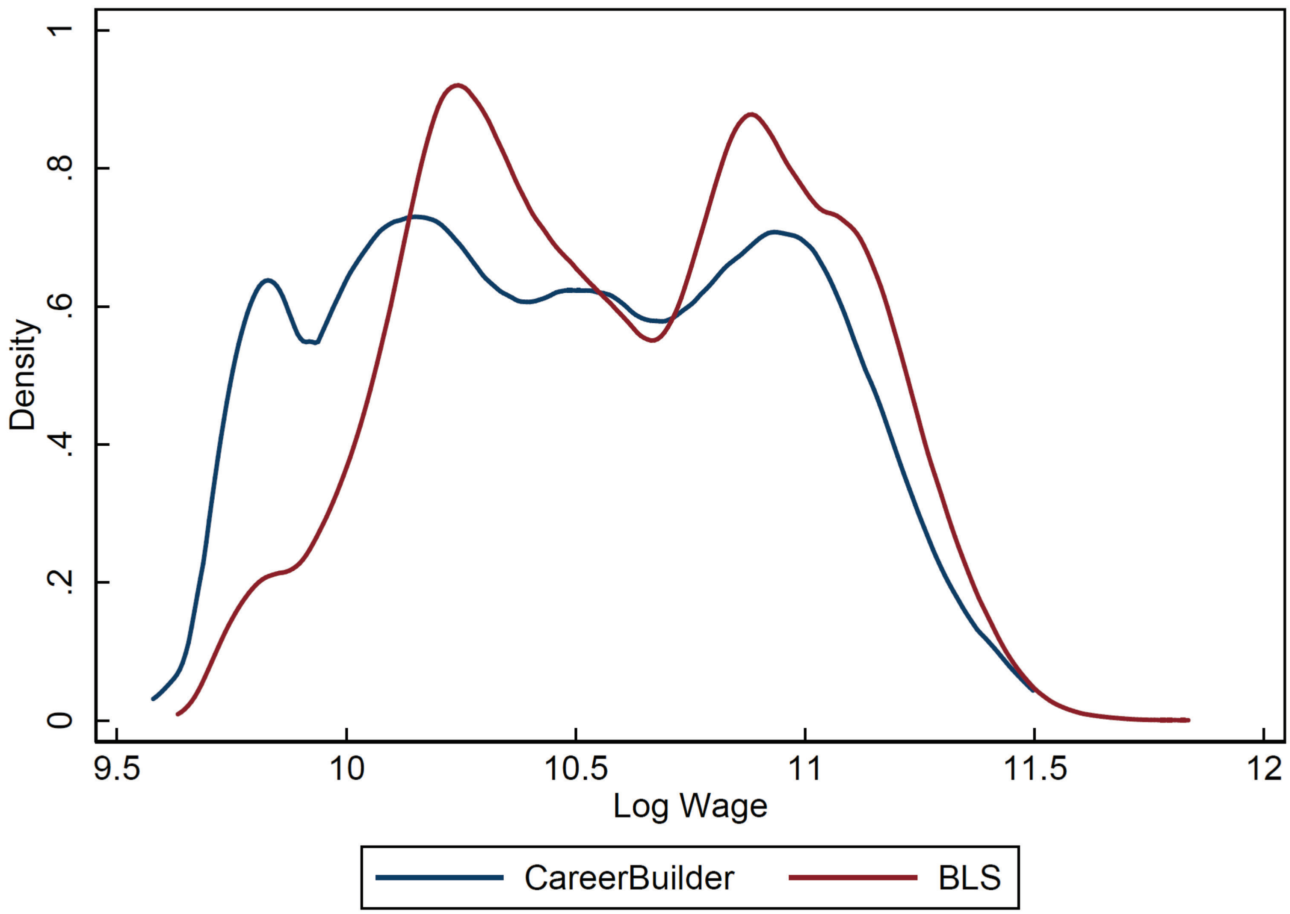


Figure 1. Log real wages across markets in CareerBuilder and BLS. This figure shows a a kernel density plot of the log real wage for labor markets over the period 2010Q1–2013Q4 on CareerBuilder.com. The real wage is defined as the average wage across wage-posting vacancies in a given market and year-quarter, divided by the consumer price index for that year-quarter. The BLS plot corresponds to the log average wages from the Occupational Employment Statistics.

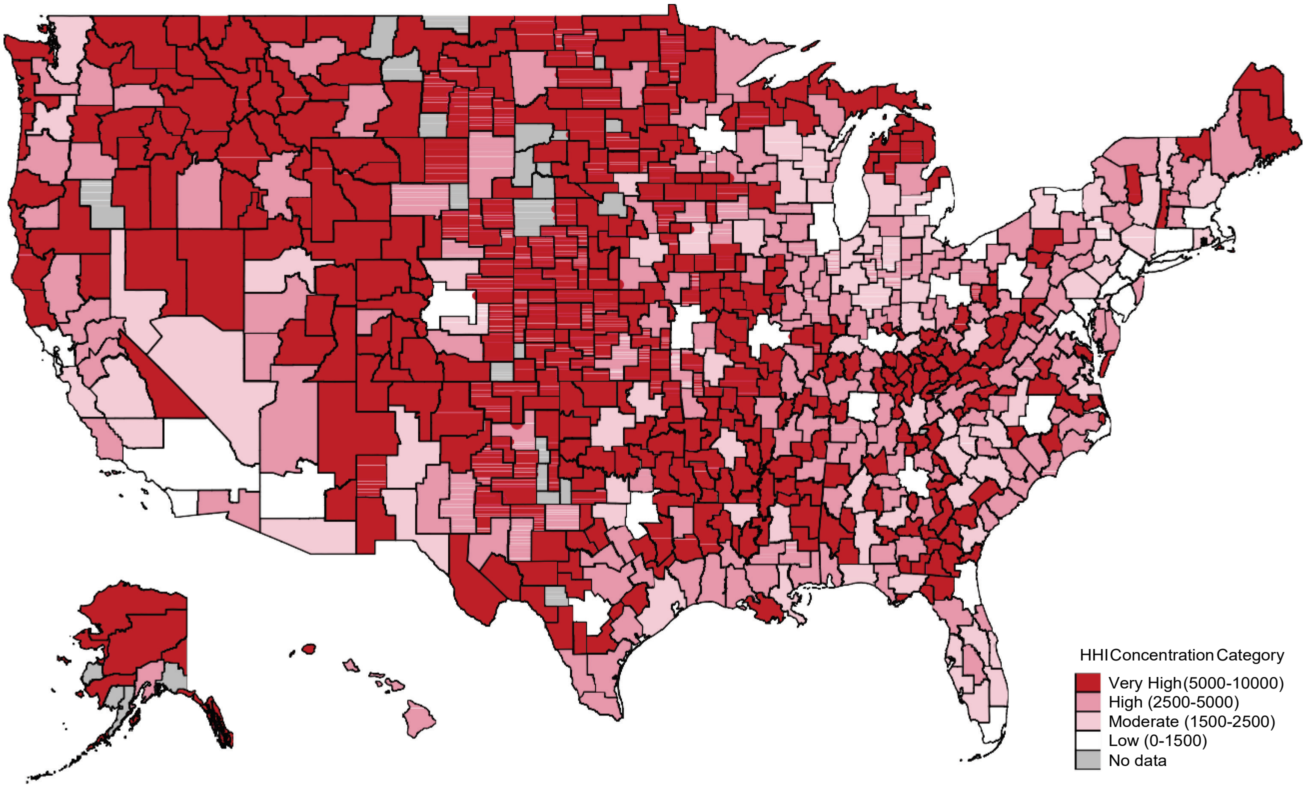


Figure 2. Average HHI by commuting zone, based on vacancy shares. This figure shows the average of the Herfindahl-Hirschman Index by 6-digit SOC occupation code for labor markets over the period 2010Q1–2013Q4. The categories we use for HHI concentration levels are: "Low": HHI between 0 and 1500; "Moderate": HHI between 1500 and 2500; "High": HHI between 2500 and 5000; "Very High": HHI between 5000 and 10000. These categories correspond to the DOJ/FTC guidelines, except that we add the additional distinction between high and very high concentration levels around the 5,000 HHI threshold. Market shares are defined as the sum of vacancies posted in CareerBuilder.com by a given firm in a given market and year-quarter divided by total vacancies posted in the website in that market and year-quarter.

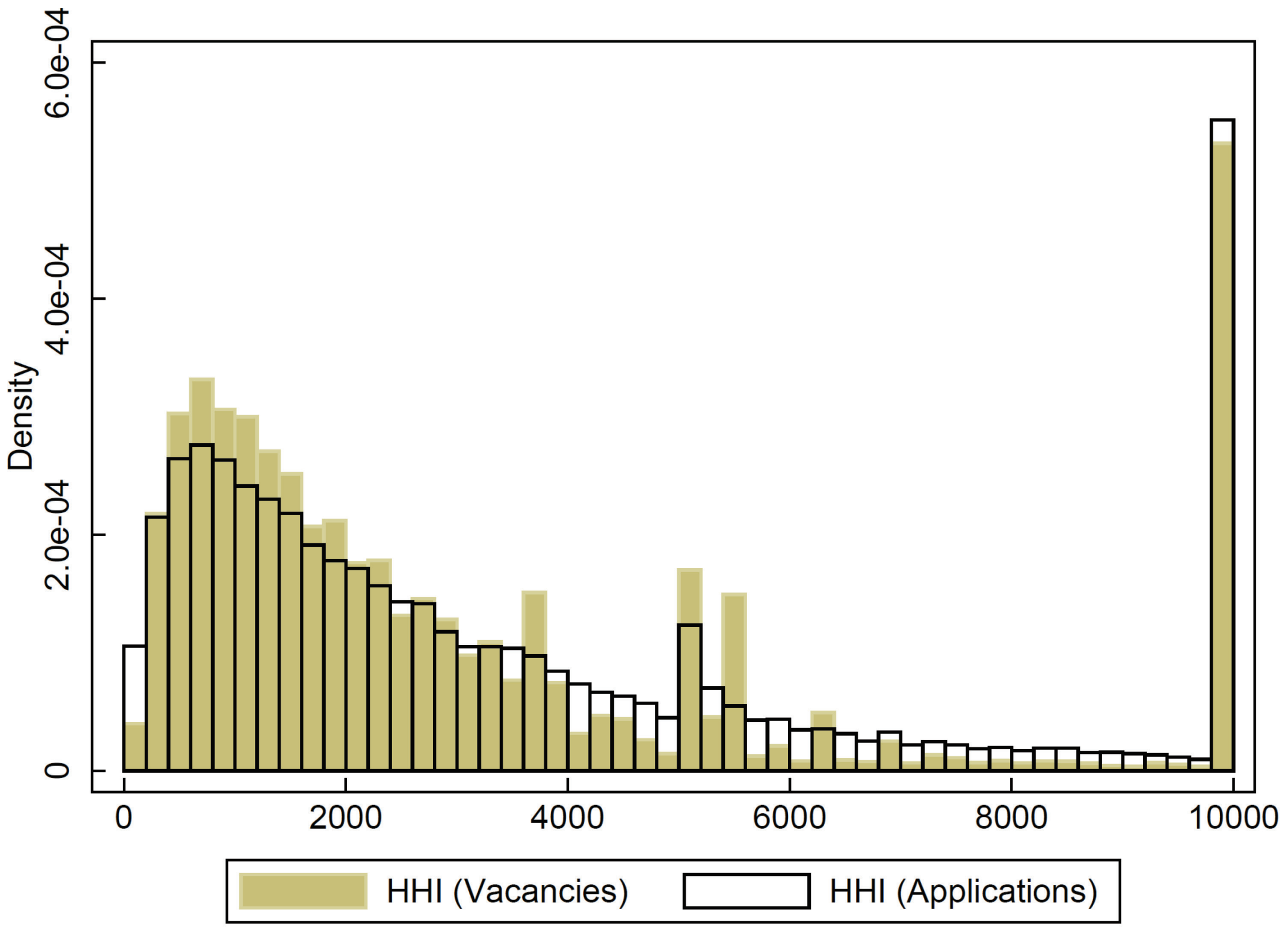


Figure 3. Histogram of HHIs based on application shares and vacancy shares. This figure shows a histogram of the Herfindahl-Hirschman Index for labor markets over the period 2010Q1–2013Q4. Market shares are defined as either the sum of vacancies posted in CareerBuilder.com by a given firm in a given market and year-quarter divided by total vacancies posted in the website in that market and year-quarter, or as the sum of applications (EOI) through the website to a given firm in a given market and year-quarter divided by the total number of applications to all firms in that market and year-quarter.

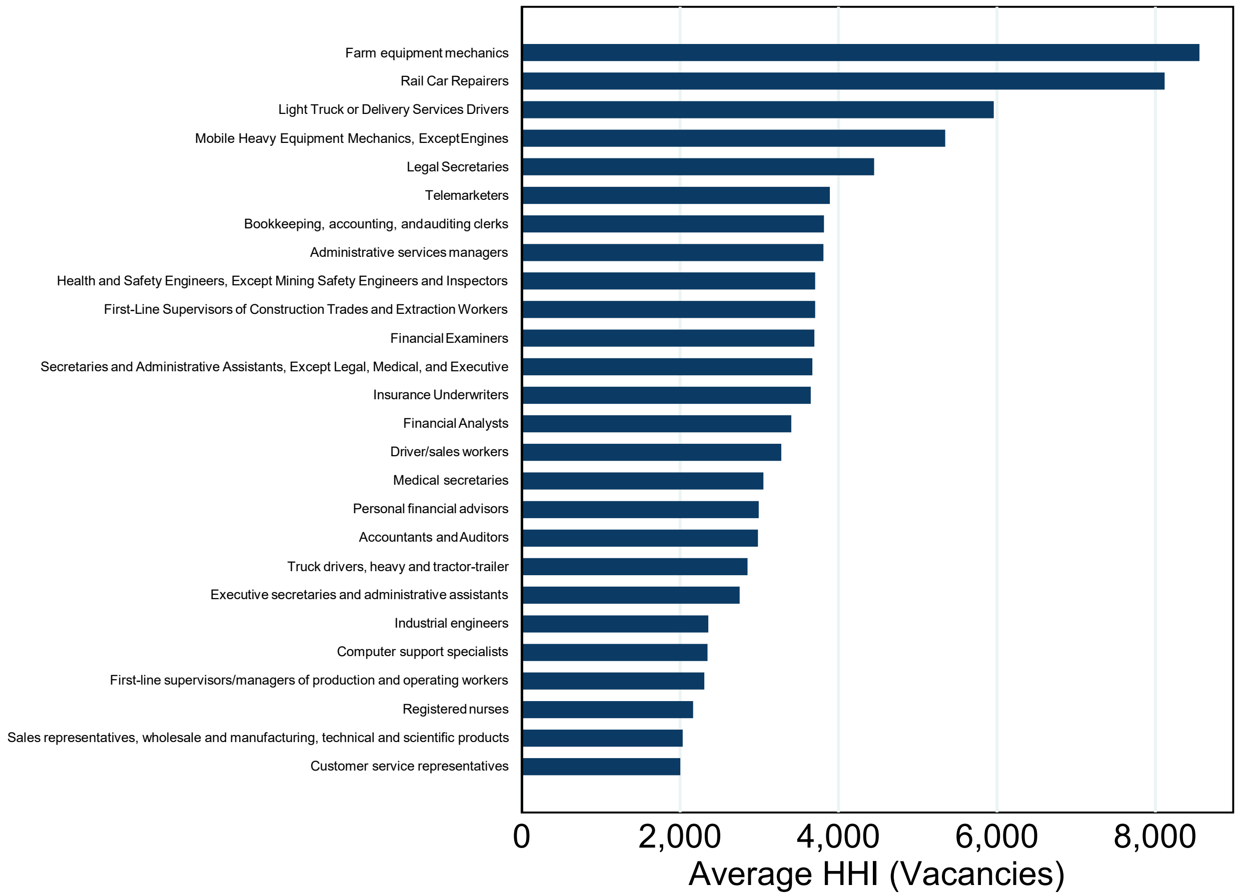


Figure 4. Average HHI by occupation, based vacancy shares. This figure shows the average of the Herfindahl-Hirschman Index by 6-digit SOC occupation code for labor markets over the period 2010Q1–2013Q4. Market shares are defined as the sum of vacancies posted in CareerBuilder.com by a given firm in a given market and year-quarter divided by total vacancies posted in the website in that market and year-quarter.

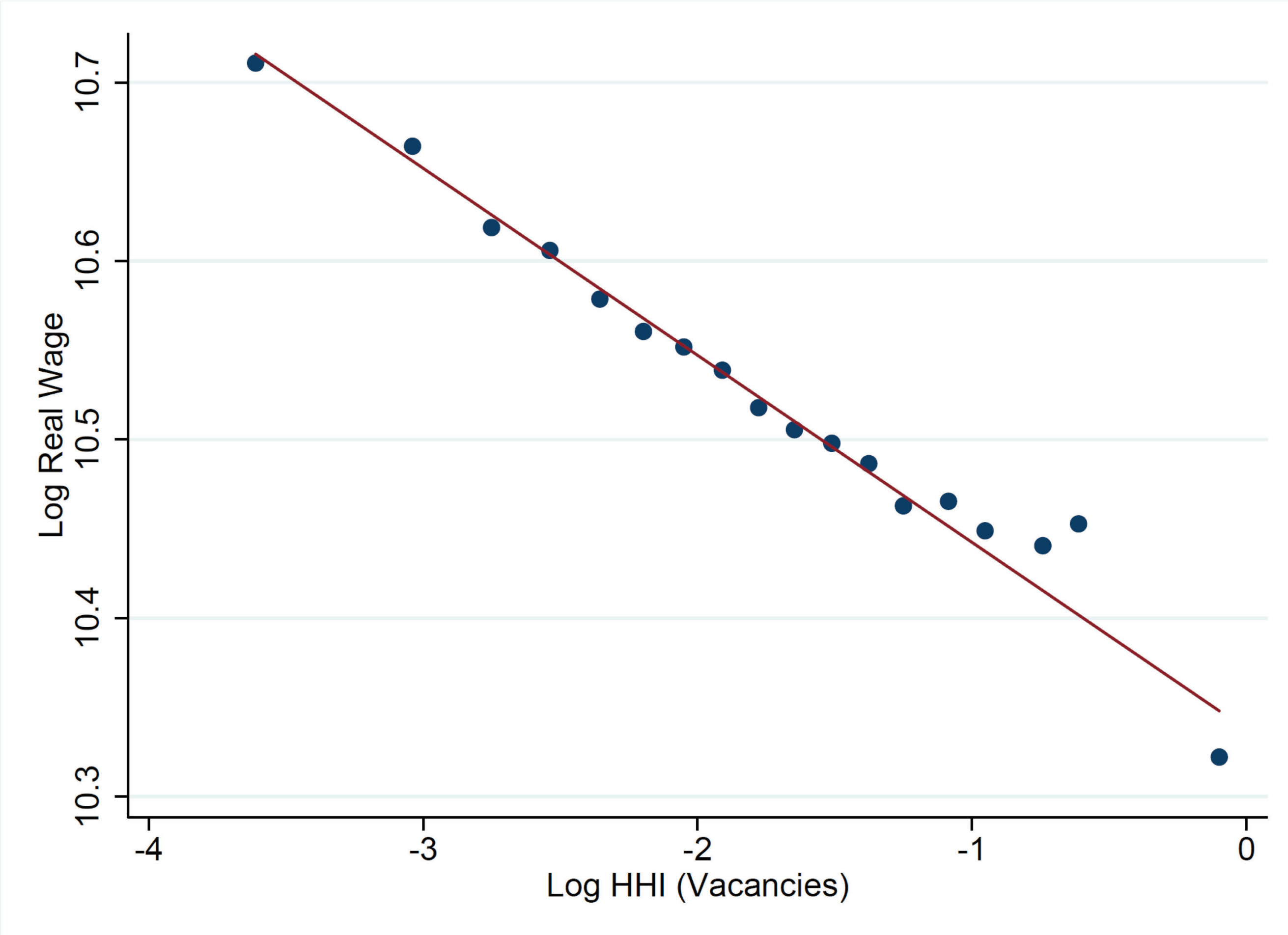


Figure 5. Binned scatter of log HHI based on vacancies and log real wage. This figure shows a binned scatter plot of log HHI based on vacancy shares and log real wage in the same market, using 18 quantiles.

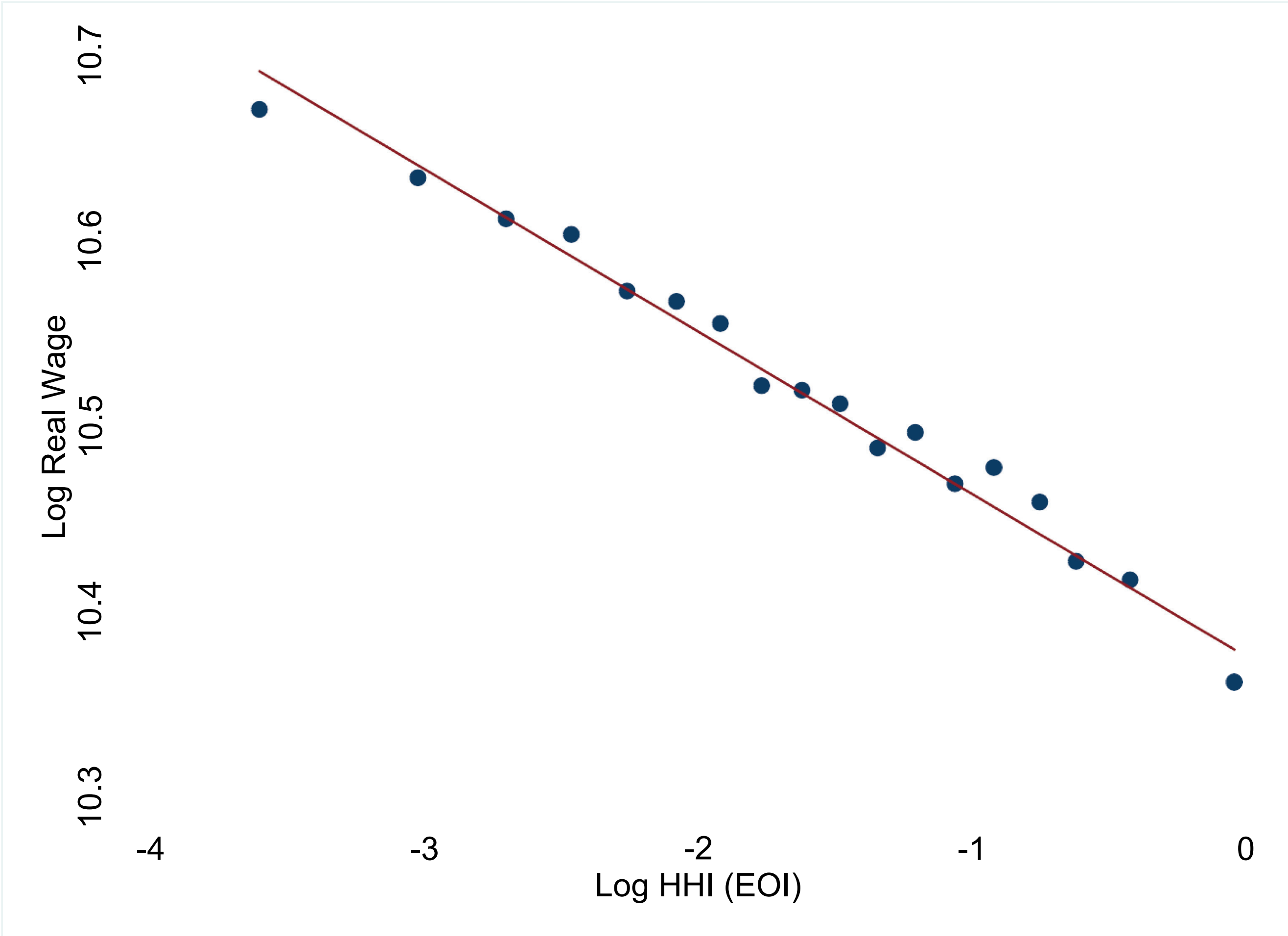


Figure 6. Binned scatter of log HHI based on applications and log real wage. This figure shows a binned scatter plot of log HHI based on application shares and log real wage in the same market, using 18 quantiles.

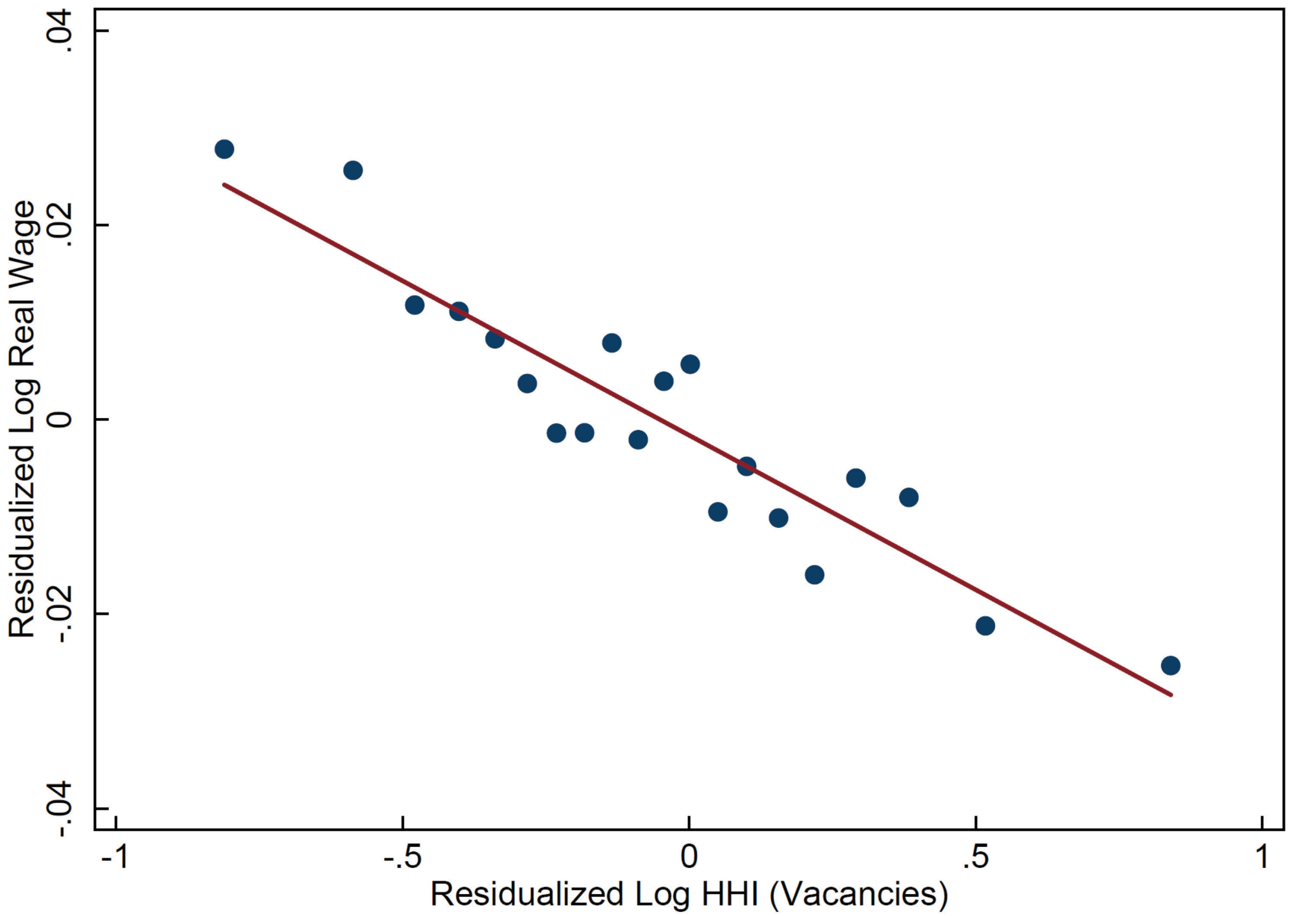


Figure 7. Binned scatter of residualized log HHI based on vacancies and residualized log real wage. This figure shows a binned scatter plot of the residuals of a regression of log HHI (based on vacancy shares) on log tightness, CZ times SOC fixed effects, and CZ times year-quarter fixed effects and the residuals of a regression of log real wage in the same market, also on log tightness, CZ times SOC fixed effects, and CZ times year-quarter fixed effects.

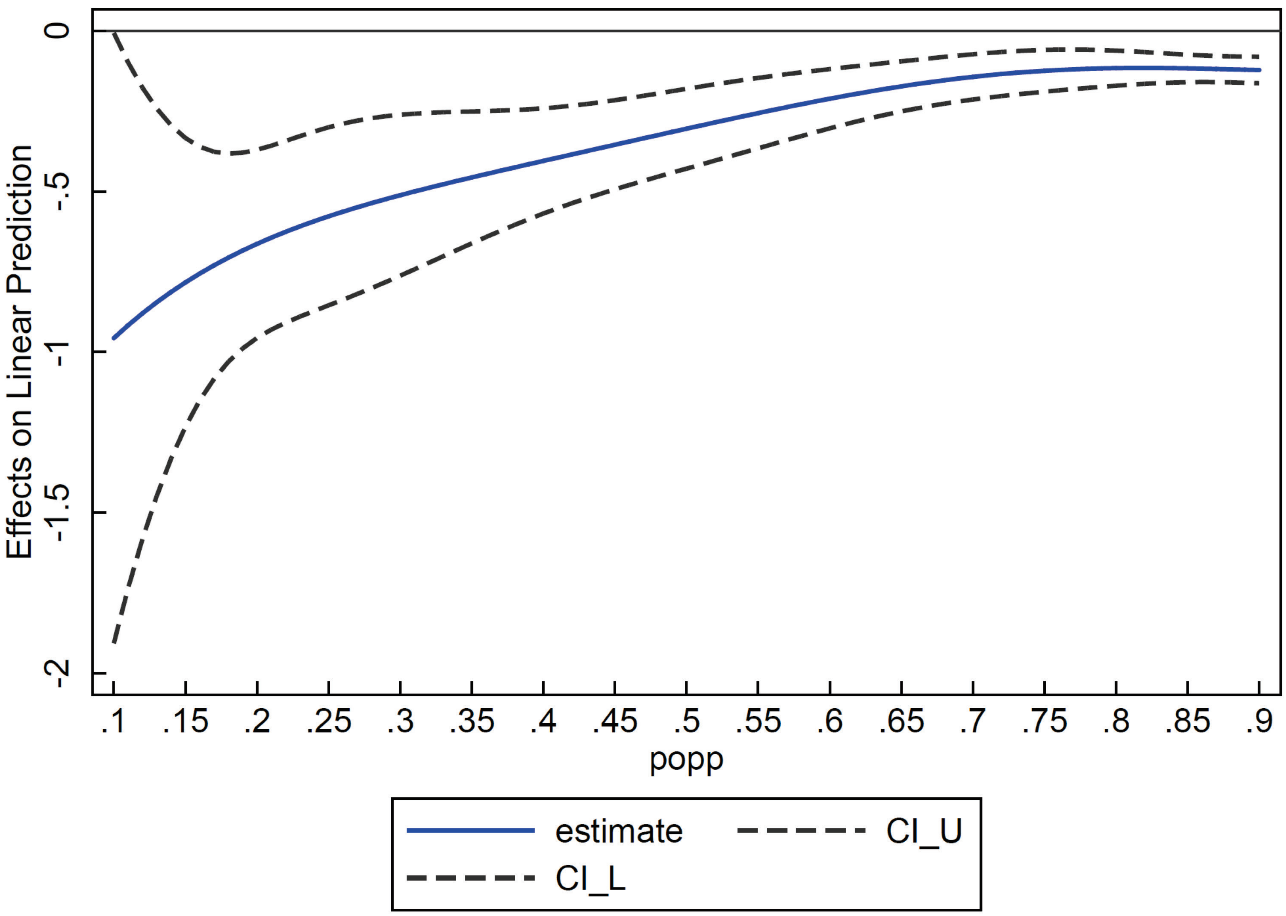
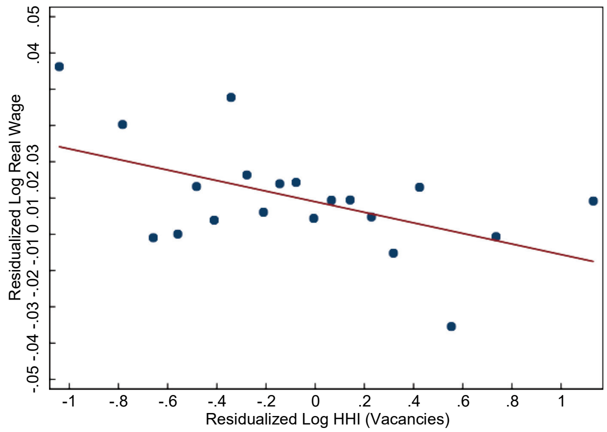
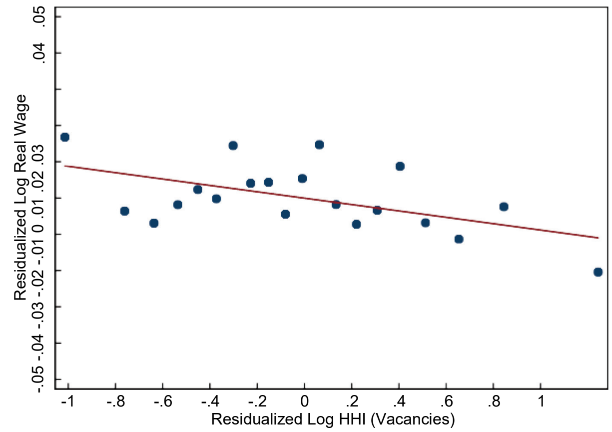


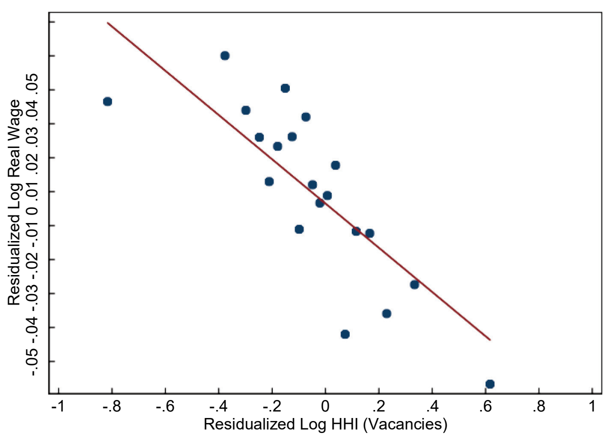
Figure 8. Effect of Log HHI (Vacancies) on Log Real Wage by Commuting Zone Population Percentile. Estimated effect from a panel IV regression of log real wage on a 5th order polynomial in log HHI (in terms of vacancies), instrumented with a 5th order polynomial in average log 1/N in other commuting zones for the same occupation, controlling for log tightness, CZ-6-digit SOC fixed effects and time fixed effects. Data are for the period 2010Q1-2013Q4. We cluster standard errors at the market level.



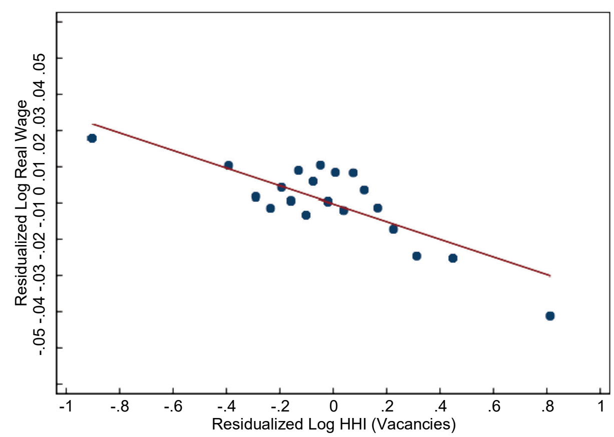
(A) CareerBuilder Wages (OLS)



(B) BLS Wages (OLS)



(C) CareerBuilder Wages (IV)



(D) BLS Wages (IV)

Figure 9. Binned scatter of residualized log HHI based on vacancies and residualized log real wage, cross-sectional variaton. Panels (A) and (B) show binned scatter plots of the residuals of a regression of log HHI (based on vacancy shares) on log tightness, CZ fixed effects and SOC fixed effects, and the residuals of a regression of log real wage in the same market, also on log tightness, CZ fixed effects and SOC fixed effects. The wages in panel (A) are from CareerBuilder, and in panel (B) from the BLS Occupational Employment Statistics. Panels (C) and (D) show binned scatter plots of the residuals of a regression of the predicted first-stage log HHI (based on vacancy shares) on log tightness, CZ fixed effects and SOC fixed effects, and the residuals of a regression of log real wage in the same market, also on log tightness, CZ fixed effects and SOC fixed effects. The predicted first-stage log HHI refers to the predicted values from a first-stage IV regression of log HHI on the average log(1/N) for the same occupation in other markets, controlling for log tightness, CZ fixed effects, and SOC fixed effects. The wages in panel (C) are from CareerBuilder, and in panel (D) from the BLS Occupational Employment Statistics.