# Measuring Labor Market Power Two Ways

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A growing literature on employer power in labor markets provides evidence for widespread monopsony (e.g. Webber (2015) Dube et al. (2019)). Much of this literature uses the elasticity of labor supply to the individual firm as a key proxy for monopsony: an elasticity that is well below infinity is a sign that employers have wage-setting power (Manning, 2011) and can pay workers less than their marginal productivity. More recently, a flurry of studies has shown a negative relationship between wages and labor market concentration of employers (Rinz, 2018; Benmelech, Bergman and Kim, 2018; Azar, Marinescu and Steinbaum, 2017; Lipsius, 2018). The labor supply elasticity and labor market concentration are both measures of labor market power, but how are they empirically related?

In this paper, we estimate a proxy for the elasticity of labor supply and investigate the relationship between this proxy and labor market concentration. We use data from the popular job posting website CareerBuilder.com to estimate firm-level wage-setting power based on the elasticity of job applications in response to variation in the posted wage. In order to deal with the endogeneity of wages, we instrument for local variation in posted wages with posted wages from the same firm in other occupations and other commuting zones. The elasticity we estimate is 0.42, a fairly low value.

We then relate our estimated application elasticities to labor market concentration, the Herfindahl-Hirshman Index based on vacancy shares. We find that, across commuting zone by 6-digit SOC

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occupation markets, the application elasticity to the firm is negatively correlated with labor market concentration. Furthermore, markets with higher concentration or lower application elasticity tend to have significantly lower wages. These findings are robust to using only within commuting zone variation across occupation, and are consistent with a theoretical framework where concentration and the labor supply elasticity are both measures of the gap between wages and productivity (Boal and Ransom, 1997). Overall, our findings suggest that higher concentration and lower application elasticity both contribute to explaining wage suppression.

We expect the application elasticity to be higher in more densely populated areas: an abundance of both jobs and workers makes these labor markets closer to the ideal of perfect competition. To test this idea, we estimate the application elasticity as a function of the population density in a commuting zone. While the application elasticity is higher in denser commuting zones, it is still below 5, which departs from perfect competition (Naidu, Posner and Weyl, 2018). This implies that even though labor market concentration is low in the most populous areas (Azar et al., 2018), the application elasticity is also low, consistent with a non-negligible degree of monopsony power.

These findings speak to two questions that have arisen in response to the research on employer power in labor markets. First, they are consistent with employer concentration being a measure of the power of employers to pay workers less than their marginal productivity. Second, they show that while employers exercise significant market power in labor markets in general, their market power does vary meaningfully with concentration. Given that concentration is a key measure for antitrust enforcement (FTC/DOJ, 2010), these findings imply that antitrust policy is a promising, if not the only, policy tool available for mitigating the monopsony power of employers.

# 1 Theoretical framework

Theory predicts that labor market concentration and the labor supply elasticity should be negatively correlated, and wages should be higher when concentration is lower and when the labor supply elasticity is higher. Assume that firms play an employment setting game under the Cournot model (for a more detailed development, see Boal and Ransom (1997)). The market wage $w$ increases with the total employment level $L$ in the market: $w(L)$. A firm chooses the level of employment to maximize profits, anticipating that higher employment leads to a higher wage for the whole market, including itself. In this model, if there are many firms, the impact of a firm's increased employment on market wages is minimal because wages are already high and close to the marginal revenue product of labor. If there are few firms, one firm's increased demand for labor increases market-level employment and wages, so equilibrium employment and wages are suppressed relative to the competitive equilibrium where wages are set equal to the marginal revenue product of labor.

The first-order condition for the firm's profit maximization gives a firm-specific rate of exploitation $E_i$:

$$E_i = \frac{MRP_i - w}{w} = \frac{L_i}{L}\varepsilon^{-1} \tag{1}$$

where $MRP_i$ is the marginal revenue product of labor in firm $i$ and $\varepsilon$ is the exogenously given market level elasticity of labor supply (i.e. the additional employment that would accrue to firms in this market if the market wage were marginally raised). Let $E$ be the employment-weighted average rate of exploitation (or wage markdown). We then have:

$$E = \sum_{i=1}^{n} E_i \frac{L_i}{L} = \varepsilon^{-1} HHI \iff HHI = \varepsilon E \tag{2}$$

where $HHI$ is the Herfindahl-Hirshman Index for employment.

Theory therefore implies that the average firm-level elasticity in a market should be negatively correlated with the HHI. Furthermore, the average inverse firm-level elasticity also measures the rate of exploitation. We expect that, for a given marginal revenue product of labor, wages are lower when HHI is higher or when the average inverse firm-level elasticity is lower.

## 2 Empirical Methods and Results

The data we use for this paper are online job postings from CareerBuilder.com, which accounts for approximately a third of all online job postings (Marinescu and Wolthoff, 2016; Azar, Marinescu and Steinbaum, 2017). For each job posting, we observe its duration, the number of applications received, the employer and its location, the Standard Occupational Classification, and the job title. Approximately 20% of the vacancies post wages.

Using this data, we measure a proxy for the labor supply elasticity to the individual firm: the elasticity of applications with respect to the posted wage. Given the theory, we expect this elasticity of applications to be negatively correlated with the HHI. Furthermore, the inverse of the application elasticity is a proxy for the market-level rate of exploitation, as defined in equation (2). Therefore, all other things equal, wages should decrease with HHI and increase with the weighted elasticity of applications.

We start by estimating the following equation in order to recover application elasticities at the firm level:

$$y_{ijmt} = w_{ijmt} \sum_{n=0}^{3} \beta_n d_m^n + \gamma \cdot x_{ijmt} + \varepsilon_{ijmt}, \tag{3}$$

where $y_{ijmt}$ is the log of the total number of applications to jobs by firm $i$ with job title $j$ in market $m$ in year-quarter $t$ and $w_{ijmt}$ is the corresponding log average wage. In line with theory, observations are weighted by each firm's vacancy share at the CZ by SOC6 by quarter, which is the level at which the HHI is computed. The $\beta_n$ coefficients estimate the firm-level application elasticity as a function of population density, allowing for a third order polynomial. The vector $x_{ijmt}$ is a set of controls, which in the baseline specification includes the log of the total number of vacancy-days that the firm posted for that job title in that market and year-quarter, year-quarter fixed effects, and CZ $\times$SOC$\times$ job title fixed effects. It is important to control for job title fixed effects as failing to do so would typically yield a negative application elasticity (Marinescu and Wolthoff, 2016).

Since the log wage is an endogenous variable, we instrument it using the average log wage for the same firm in other CZ $\times$ SOC markets (in the spirit of Hausman, Leonard and Zona (1994)).

This average excludes wages in the same CZ for other SOCs, or wages for the same SOC in other CZs. Wages posted in other labor markets might be a good instrument because of firm-level wage-setting policies that hold across the labor markets out of which a given firm hires (Card et al., 2016). Local job-posting and wages may be jointly determined by local labor supply and demand conditions, but national firm-level wage-setting in the excluded markets is unlikely to be caused by an omitted variable at the market level and can hence be used to trace out the application elasticity.

To allow for elasticities that vary more flexibly than just as a function of CZ population density, we estimate separate regressions for each CZ $\times$ SOC market. We do this in two steps, which are equivalent to interacting the wage with a CZ $\times$ 6-digit SOC dummy variable for each market and using the instrument for the wage (also interacted with dummy variables for each market). In the first step, we run three regressions using data for all markets and controlling for log days posted, CZ $\times$ 6-digit SOC $\times$ job title fixed effects, and year-quarter fixed effects: the left-hand side variables are log applications, log wage and the instrument. For each of these three regressions, we obtain residuals. In the second step, we run, separately for each CZ $\times$ SOC, a simple regression of residualized log applications on residualized log wage, instrumented by residualized average log wage for the same firm in other CZs and other SOCs. This gives us an estimate of the applications elasticity for each CZ $\times$ SOC.

Figure 1 depicts the relationship between firm-level application elasticity and population density as estimated in equation 3. In commuting zones between the 20th and the 80th percentile of population density (weighted by employment levels), the application elasticity is not significantly different from zero; in markets below the 20th percentile of population density, the elasticity appears to be negative, for reasons that are yet to be investigated. Overall, the results are consistent with 80% of workers working in markets with substantial monopsony power. Above the 80th percentile of the population density, the application elasticity increases with population density, reaching about 4 for the most densely populated areas. Even the most densely populated areas have nowhere near an infinite elasticity of applications with respect to the posted wage.

We then use those elasticities as the dependent variable in two cross-sectional regressions.

Since it is difficult to reliably estimate an elasticity for very small markets, we restrict the sample to CZ-SOCs with at least 50 observations. To account for the uncertainty around the elasticity estimate, observations are weighted by the inverse variance of the estimated elasticities. Finally, observations with elasticities above the 99th percentile and below the 1st percentile of the distribution are dropped from the sample.

In the first cross-sectional regression, we examine the relationship between the application elasticity estimated by the residualized regressions described above and the HHI computed from each firm's share of posted vacancies in the market defined by commuting zone, SOC-6 occupation, and quarter (averaged by commuting zone-by-SOC6; see Azar et al. (2018) for a more in-depth discussion of this market definition). We verify that the elasticity increases with population density: the relationship is positive but not statistically significant (Table 1, col. 1). As predicted by theory, a higher concentration of employers is negatively associated with the application elasticity (col. 2). This suggests that concentration is a contributing factor to firm-level wage-setting power. The concentration-application elasticity relationship is unaffected when we include population density as an explanatory variable for the application elasticity (col. 3). The relationship between the application elasticity and the HHI also holds across occupations within a commuting zone (col. 4).

In the second cross-sectional regression, we regress observed market-level wages (again averaged by commuting zone-by-SOC6) on estimated application elasticities and concentration by labor market. Table 2 shows that the application elasticity and concentration are each, separately, correlated with posted wages, with the expected signs. Furthermore, when entered together the application elasticity and concentration both retain their significant effect on wages (column 3), with similar magnitudes. In column 4, we include commuting zone fixed effects, and the results are robust: this shows that the cross-sectional relationship between wages and the two measures of market power is not driven by differential costs of living across geographies or other factors such as productivity that vary systematically across commuting zones.

# 3 Discussion and conclusion

In this paper, we estimate the firm-level application elasticity from job-posting data, and we relate our estimates to labor market concentration. The results indicate that labor market concentration is negatively correlated with the application elasticity, and the application elasticity is close to zero in most markets but the most densely-populated. Wages are lower in markets where the application elasticity is lower or labor market concentration is higher, and this relationship persists when comparing occupations within a commuting zone. The results are consistent with the application elasticity and labor market concentration being two measures of labor market power

Our results also suggest that while that power is likely to be pervasive in labor markets, it could respond to competition policy. This is in contrast to the idea that the power imbalance between employers and workers is such that anti-concentration policy would be powerless against it. The reality is more nuanced: employers do enjoy unilateral power to set wages, but that is reinforced by a lack of competition for labor in the markets where they hire. Therefore, antitrust and competition policy has the potential to increase wages by policing anticompetitive conduct in the labor market, including issues like non-competition agreements and mergers (Marinescu and Hovenkamp, 2018; Naidu, Posner and Weyl, 2018).

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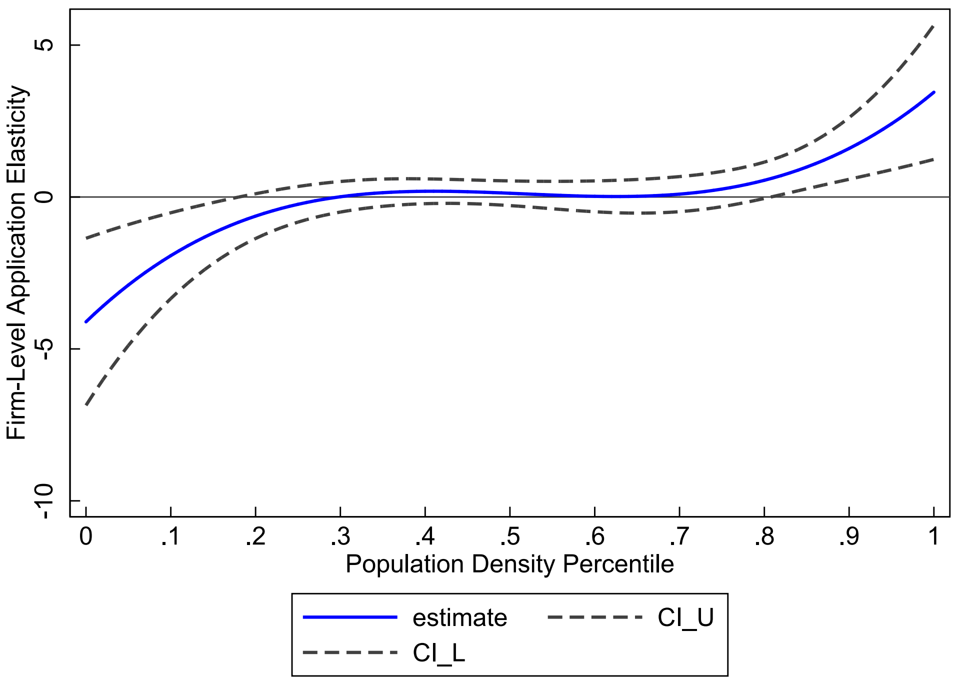


**Figure 1.** Firm-level application elasticity as a function of Commuting Zone population density.

Estimated effect from a panel IV regression of log EOI on the log real wage interacted with a 3rd order polynomial in log population density. The wage is instrumented with the average log real wage in other commuting zones and other SOCs for the same firm interacted with a 3rd order polynomial in log population density. We control for log days posted, CZ $\times$ 6-digit SOC $\times$ job title fixed effects and year-quarter fixed effects. Data are for the period 2010Q1-2013Q4. We cluster standard errors at the CZ$\times$ 6-digit SOC level.

**Table 1.** Application elasticity regressions.

| | Application Elasticity | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log Population Density | 0.0649 | | 0.0162 | |
| | (0.0628) | | (0.0641) | |
| Log HHI | | -0.219*** | -0.215*** | -0.218** |
| | | (0.0659) | (0.0679) | (0.105) |
| CZ Fixed Effects | | | | ✓ |
| Observations | 500 | 500 | 500 | 474 |
| R-squared | 0.002 | 0.022 | 0.022 | 0.350 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Data are for the period 2010Q1-2013Q4, aggregated by CZ-SOC. We restrict the sample to CZ-SOCs with at least 50 observations. Observations are weighted by the inverse variance of the estimated elasticities, and observations with elasticities above the 99th percentile and below the 1st percentile of the distribution are dropped from the sample.

**Table 2.** Wage regressions.

| | Log Real Wage | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\eta_m$ | 0.103*** | | 0.0996*** | 0.115*** |
| | (0.0112) | | (0.0113) | (0.0116) |
| Log HHI | | -0.0576*** | -0.0358** | -0.0545** |
| | | (0.0178) | (0.0167) | (0.0238) |
| CZ Fixed Effects | | | | ✓ |
| Observations | 500 | 500 | 500 | 500 |
| R-squared | 0.146 | 0.021 | 0.154 | 0.555 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Data are for the period 2010Q1-2013Q4, aggregated by CZ-SOC. We restrict the sample to CZ-SOCs with at least 50 observations. Observations are weighted by the inverse variance of the estimated elasticities, and observations with elasticities above the 99th percentile and below the 1st percentile of the distribution are dropped from the sample.

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