
Labor Market Competition and Employment Adjustment over the Business Cycle

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ABSTRACT


Using linked employer–employee data that covers the majority of U.S. employment, I examine how frictions in the labor market have evolved over time. I estimate that the labor supply elasticity to the firm declined significantly (1.20–1.01) since the late 1990s, with the steepest declines occurring during the financial crisis. I find that this decline in labor market competition led to at least a 4 percent drop in earnings for the average worker. I also find evidence that relatively monopsonistic firms smooth their employment behavior, growing at a rate lower than relatively competitive firms in good economic climates and slightly higher during poor economic climates. This conforms with the predictions of recent macroeconomic search models that suggest frictions in the economy may actually reduce employment fluctuations due to adjustment costs associated with hiring and laying off workers.

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I. Introduction

The severe labor market downturn experienced during the Great Recession was the worst seen by the United States in 70 years. At its peak, the national unemployment rate was 10.6 percent, the average duration of unemployment reached 35 weeks, and nearly one in six workers lost their job (Farber 2011). Labor market churn, an important ingredient to a dynamic labor market declined markedly during this period (Lazear and Spletzer 2012). Each of these factors implies that the competition between firms for a given worker's services declined markedly during the Great Recession. For many who lost their jobs, firms were competing with reservation wages (that is, unemployment insurance) rather than with the wages of other firms. Taking a longer view of the labor market, workers have received a declining share of total income generated by firms. This started out as a very slow decrease over the latter half of the 20th century, followed by a steep drop in the early 2000s.

Recent research (Hirsch, Schank, and Schnabel 2010; Ransom and Oaxaca 2010; Depew and Sorensen 2013; Booth 2014; Webber 2015; Naidu, Nyarko, and Wang 2016; Hirsch, Jahn, and Schnabel 2018; Dube, Giuliano, and Leonard 2019) has highlighted both the prevalence and importance of frictions in the labor market that lead to less than perfect mobility for workers. While this relatively new strand of the literature on labor market competition has been largely agnostic about the causes of these market frictions (for example, asymmetric information, moving costs, employer concentration, low job offer arrival rate, etc.), the conclusion that significant frictions exist has been consistent.

Using linked employer–employee data from the U.S. Census Bureau, I estimate the decline in labor market competition (as measured by the labor supply elasticity facing the firm) that workers experienced between 1998 and 2012 and evaluate the impact this decline had on the earnings of the average worker. Additionally, I examine the interaction between the degree of labor market competition firms experience and their employment behavior (for example, hiring, separations).

This study contributes to the literature in two important ways. First, it is the only study to examine the time-series variation in the labor supply elasticity for a comprehensive set of U.S. firms.¹ Second, this is the first paper to compare the employment behavior (hires, separations, growth, etc.) of firms in competitive versus monopsonistic labor markets.

I find that the labor supply elasticity to the firm is procyclical and that the average elasticity faced by workers declined by 16 percent from its peak (1.20) to a low of 1.01 in late 2010. I conclude that this decline in labor market competition led to earnings losses of approximately 4 percent—this is in addition to lower baseline earnings due to the high baseline level of firm market power documented below and in the recent literature. I also find large differences in the decline of labor market competitiveness across industries, with professional/scientific/technical services experiencing the largest drop in competition. This decline in labor market competitiveness is important for both researchers and policymakers. While the decline of the labor share of income has been well studied, little evidence to date has been able to connect labor market monopsony power to this trend. Changes in the labor supply elasticity of the magnitude measured in this

1. A recent excellent study Hirsch, Jahn, and Schnabel (2018) examines time series variation in the labor supply elasticity of German firms.

manuscript suggest this link deserves further study. From a practical policymaking perspective, worker welfare (and overall economic efficiency) is substantially reduced at labor supply elasticities in the range that I measure, though more work is necessary to identify the drivers of contemporary monopsony power because the optimal policy response is heavily dependent on the source of the frictions.

I find that in a strong economy firms in less competitive labor markets have lower growth rates than firms in relatively more competitive labor markets. This appears to be due to a higher separation rate rather than a lower hiring rate. Furthermore, I find that during the Great Recession relatively monopsonistic firms had a slightly higher growth rate than firms in more competitive markets. Taken together, these results suggest that monopsonistic firms are more able (due to their increased market power) to smooth their employment behavior over the business cycle, implying that frictions in the economy may actually reduce employment volatility. This conforms with predictions from the search theory literature (Rogerson and Shimer 2011), which finds that when labor adjustment costs are large enough, firms would rather not lay off workers during a downturn, knowing that eventually they would want to hire them back. Firms in relatively competitive markets are more exposed to market forces and are thus less able to survive a recession without making significant cutbacks.

The paper is organized as follows: Section II describes the previous literature on competition in the labor market. Section III lays out the theoretical foundation for this study. The data and methods are described in Section IV. Section V presents the results, and Section VI concludes.

II. Previous Literature

The concept of “monopsony” was first analyzed in a theoretical context by Robinson (1933). Although the term is most often used in a labor market context, it can also refer to a firm that is the only buyer of an input. In the “dynamic monopsony” framework, developed and popularized in Manning (2003), the word monopsony is effectively synonymous with the following phrases: monopsonistic competition, oligopsony, employer wage-setting power, imperfect competition, finite labor supply elasticity, or upward sloping labor supply curve to the firm.

In the classic monopsony framework, a single firm was the only outlet for which workers could supply labor. However, just as with the monopoly model in product markets, a single-firm monopsony model does not do a good job of accurately characterizing labor markets. Under the new framework, monopsony power is thought of as any departure from the assumptions of perfect competition. The degree of latitude that employers have in setting wages themselves (rather than accepting the market wage) may vary significantly across labor markets, and even across firms within a given labor market.

Many studies have provided suggestive evidence of a less than perfectly competitive labor market. The existence of significant firm effects in wage regressions, even after controlling for detailed person and industry characteristics, is cited as strong suggestive evidence of firm market power (Abowd, Kramarz, and Margolis 1999; Goux and Maurin 1999). Goux and Maurin (1999) find that firm-level heterogeneity impacts an

individual's wage by more than 20 percent. Goux and Maurin (1999) also find that firm effects are more strongly linked to firm characteristics such as size rather than productivity, implying that the firm effects are not simply a proxy for workers' unmeasured marginal product of labor. More recent work has found that lower levels of competition weaken the link between worker pay and productivity (Card et al. 2018). Even the lack of large disemployment effects found in the voluminous minimum wage literature (see, for example, the pioneering work by Card and Krueger 1995) can be viewed as indirect evidence of an imperfectly competitive labor market.

Most of the theoretical work relating to monopsony resides in the search theory literature, with major contributions coming from Burdett and Mortensen (1998) and Shimer (2005).² A frictional labor market served as the underpinning for Alan Manning's seminal reanalysis of labor economics absent the assumption of perfect competition (Manning 2003).

Recent empirical studies have attempted to directly estimate the average slope of the labor supply curve faced by the firm, which is a distinct concept from the market labor supply elasticity.³ Studying the market for nurses, Sullivan (1989) finds evidence of monopsony using a structural approach to measure the difference between nurses' marginal product of labor and their wages. Examining another market commonly thought to be monopsonistic, the market for schoolteachers, Ransom and Sims (2010) instrument wages with collectively bargained pay scales and estimate a labor supply elasticity between 3 and 4. Looking at the same market, Bahn (2015) finds evidence of significant search frictions and also connects worker immobility in part to occupations with a large "caring" component.

In a novel approach using German administrative data, Schmieder (2013) finds evidence of a positive sloping labor supply curve through an analysis of new establishments. In a developing country context, Brummund (2011) uses a structural production function approach and finds strong evidence of monopsony in Indonesian labor markets, estimating labor supply elasticities between 0.6 and 1. A number of excellent more recent papers also find strong evidence that firms have significant wage-setting power (Naidu, Nyarko, and Wang 2016; Azar, Marinescu, and Steinbaum 2022; Dube, Manning, and Naidu 2018; Dube, Naidu, and Suri 2020).

Several recent papers use a dynamic approach similar to this study to estimate the average labor supply elasticity to the firm. For an excellent meta-analysis of this literature, please see Sokolova and Sorensen (2018). In some cases, this analysis is carried out for a single or small set of firms (Ransom and Oaxaca 2010; Depew and Sorensen 2013; Depew, Norlander, and Sorensen 2017), and in others for broader labor markets (Manning 2003; Hirsch, Schank, and Schnabel 2010; Hirsch and Jahn 2015; Webber 2015, 2016; Bachmann and Frings 2017; Hirsch, Jahn, and Schnabel 2018). Each paper finds evidence of significant frictions, although they vary by many factors, including geography, industry, and the type of workers being studied. In addition to the general importance of documenting the magnitude of these elasticities on theoretical grounds (see Booth 2014 for a good discussion), Dupuy and Sorensen (2014) show that falsely

2. See Mortensen (2003) or Rogerson, Shimer, and Wright (2005) for a review of this literature.

3. The market labor supply elasticity corresponds to the decision of a worker to enter the labor force, while the labor supply elasticity to the firm corresponds to the decision of whether to supply labor to a particular firm. This paper focuses on the firm-level decision.

assuming a perfectly competitive input (labor) market will lead to biased estimates of production function parameters.

Little theoretical work has been done regarding the impact of labor market frictions over the business cycle. However, Rogerson and Shimer (2011) show that the presence of search frictions in an economy reduces the fluctuations in employment because firms are less constrained to follow the rest of the economy and choose to smooth their employment behavior to save on potentially large labor adjustment costs.

III. Theoretical Model

The seminal Burdett and Mortensen (1998) search model elegantly illustrates how, even assuming equal ability for all workers, wage dispersion is an equilibrium outcome under the assumption that the arrival rate of job offers is positive but finite (perfect competition characterizes the limiting case, as the arrival rate tends to infinity). While I do not explicitly estimate the Burdett and Mortensen model in this paper, the intuition of monopsony power derived from search frictions is central to this study. See Kuhn (2004) for a critique of the use of equilibrium search models in a monopsony context.

With the Burdett and Mortensen model of equilibrium wage dispersion as our starting point, assume there are M_l equally productive workers (where productivity is given by p), each gaining utility b from leisure. Further assume there are M_e constant returns to scale firms, which are infinitesimally small when compared to the entire economy. A firm sets wage w to maximize steady-state profits $\pi = (p - w)N(w)$, where $N(w)$ represents the supply of labor to the firm. Let $F(w)$ be the *cdf* of wage offers observed in the economy, and $f(w)$ is the corresponding *pdf*. All workers within a firm must be paid the same wage. Employed workers will accept a wage offer w' if it is greater than their current wage w , and nonemployed workers will accept w' if $w' \geq b$, where b is their reservation wage. Wage offers are drawn randomly from the distribution $F(w)$ and arrive to all workers at rate λ . Assume an exogenous job destruction rate δ and that all workers leave the job market at rate δ to be replaced in nonemployment by an equivalent number of workers. R^N denotes The recruitment flow and separation rate functions are given by:

$$(1) \quad R(w) = R^N + \lambda \int_0^w f(x)N(x)dx$$

$$(2) \quad s(w) = \delta + \lambda[1 - F(w)]$$

Burdett and Mortensen (1998), or alternatively Manning (2003), show that in this economy, as long as λ is positive and finite, there will be a nondegenerate distribution of wages even when all workers are equally productive. As λ tends to zero, the wage distribution collapses to the monopsony wage, which in this economy would be the reservation wage b . As λ tends to infinity the wage distribution collapses to the perfectly competitive wage, the marginal product of labor p . The following primarily relies on the model presented in Manning (2003) (which itself builds off of Burdett and Mortensen 1998) to derive a formulation for the labor supply elasticity facing the firm, which researchers can take to data.

The supply of labor to a firm can be described recursively with the following equation, where $R(w)$ is the flow of recruits to a firm and $s(w)$ is the separation rate.

$$(3) \quad N_t(w) = N_{t-1}(w)[1 - s_{t-1}(w)] + R_{t-1}(w)$$

Equation 3 says that a firm's employment this period is equal to the fraction of workers from last period who stay with the firm, $N_{t-1}(w)[1 - s_{t-1}(w)]$, plus the number of new recruits. Assuming a steady state for simplicity,⁴ we can rewrite Equation 3 as

$$(4) \quad N(w) = \frac{R(w)}{s(w)}$$

Taking the natural log of each side, multiplying by w , and differentiating, we can write the elasticity of labor supply to the firm, ε , as a function of the long-run elasticities of recruitment and separations.

$$(5) \quad \varepsilon = \varepsilon_R - \varepsilon_S$$

We can further decompose the recruitment and separation elasticities in the following way

$$(6) \quad \varepsilon = \theta^R \varepsilon_R^E + (1 - \theta^R) \varepsilon_R^N - \theta^S \varepsilon_S^E - (1 - \theta^S) \varepsilon_S^N$$

where the elasticity of recruitment has been broken down into the elasticity of recruitment of workers from employment (ε_R^E) and the elasticity of recruitment of workers from nonemployment (ε_R^N). Similarly, the elasticity of separation has been decomposed into the elasticity of separation to employment (ε_S^E) and the elasticity of separation to nonemployment (ε_S^N). θ^R and θ^S represent the share of recruits from employment and the share of separations to employment, respectively.

While there are established methods for estimating separation elasticities with standard job-flow data, recruitment elasticities are not identified without detailed information about every job offer a worker receives. Therefore, it would be helpful to express the elasticities of recruitment from employment and nonemployment as functions of estimable quantities.

Looking first at the elasticity of recruitment from employment, we can write the elasticity of recruitment from employment as a function of estimable quantities (a detailed derivation can be found in Manning 2003):

$$(7) \quad \varepsilon_R^E = \frac{-\theta^S \varepsilon_S^E}{\theta^R}$$

Next, Manning (2003, p. 100) notes that the elasticity of recruitment from nonemployment can be written as

$$(8) \quad \varepsilon_R^N = \varepsilon_R^E - w \theta'^R(w) / \theta^R(w) [1 - \theta^R(w)]$$

4. For all analyses, parameters are estimated flexibly and allowed to vary over time. Conceptually, this is not a relaxation of the steady-state assumption, but rather allows firms to transition to new steady states as conditions changes.

This is derived from the definition of θ^R , the share of total recruits from employment, which implies $R^N = R^E(1 - \theta^R)/\theta^R$, where R^N and R^E are the recruits from nonemployment and employment, respectively. Taking the natural log of each side of this relation and differentiating yields the relation depicted in Equation 8. The second term on the right-hand side of Equation 8 can be thought of as the bargaining premium that an employee receives from searching while currently employed. Thus, the labor supply elasticity to the firm can be written as a function of both separation elasticities, the premium to searching while employed, and the calculated shares of separations and recruits to/from employment. In order to relax the assumption of a time-invariant labor supply elasticity, I also estimate the model by interacting each parameter with quarter fixed effects (described below).

It is important to note that imperfect competition in the labor market can arise from many different factors, not all of which are well represented in the assumptions of the Burdett and Mortensen model. For example, a worker being unable to move to a new job due to individual-specific factors, such as a compensating differential (for example, a flexible work schedule that allows you to care for your children), is better motivated by wage-bargaining models with an individual-specific match component. The estimation strategy derived from the Burdett and Mortensen model allows for such individual-specific factors to influence the labor supply elasticity, but is unable to identify the source of any labor market frictions. An excellent reconciliation of the different models of firm wage-setting power can be found in Card et al. (2018).

IV. Data and Methodology

A. Data

The Longitudinal Employer Household Dynamics (LEHD) data are built primarily from Unemployment Insurance (UI) wage records, which cover approximately 98 percent of wage and salary payments in private-sector nonfarm jobs. Information about firms is constructed from the Quarterly Census of Employment and Wages (QCEW). The LEHD infrastructure allows users to follow both workers and firms over time, as well as to identify workers who share a common employer. Firms in these data are defined at the state level, which means that a Burger King in Indiana and a Burger King in Ohio are considered to be different firms, but all Burger Kings in Ohio are considered to be part of the same firm. These data also include demographic characteristics of the worker and basic firm characteristics, obtained through administrative record and statistical links. For a complete description of these data, see Abowd et al. (2009).

There are two distinct samples I use in this study. First, I analyze a set of employment spells to obtain estimates of the labor supply elasticity for each firm. This sample is constructed in a similar way to Webber (2015) and Webber (2016) (although the sample is slightly different because this study uses fewer states, but more years of data). The second sample comprises the set of firms for which a labor supply elasticity is estimated.

The sample of employment spells consists of quarterly observations on earnings and employment for 31 states between 1998 Quarter 1 and 2012 Quarter 1.⁵ These are

5. The states in my sample are AK, AZ, CO, CA, FL, GA, HI, ID, IL, IN, KS, KY, LA, MD, ME, MN, MO, MT, NC, NJ, NM, NY, OR, PA, RI, SD, TX, WA, WI, WV, and WY.

chosen in order to have a consistent panel of states for all years of my sample and thus avoid conflating changes in firm characteristics with composition changes (16 other states do not enter the LEHD infrastructure until after 1998). My sample covers approximately 75 percent of total U.S. private/nonfarm employment during the span of the data.

Given that the identifying variation for the labor supply elasticities comes from job separations (including whether a worker separates to employment or nonemployment), it is a potential problem that some states are not available. I could be misclassifying true separations to employment (moving from a state within my sample to an employer in a different state outside my sample) as separations to nonemployment. This type of missing data has been shown to bias estimates of the returns to education in cases where only one state's UI data are used (Foote and Stange 2019). To assess the importance of this restriction, I reestimated the elasticities using only post-2003 data, when data from nearly all additional states are available. Comparing the elasticity estimates when I am able to correctly classify virtually all of the separations versus those where I do not yields no discernible (within the first two decimal places) difference in results.

The administrative nature of the data used in this study presents an interesting measurement problem, as any payment between a firm and an individual is included. In many cases, these payments do not constitute the same kind of employment relationship that is measured in surveys. For example, if I were to write an op-ed for my local newspaper and be paid a small fee, this would appear in my sample as an employment spell lasting one quarter with earnings equal to the fee. Even in the case of a typical job, there is very often back pay that is transmitted to the worker several quarters after the end of their employment spell. I thus cannot perfectly distinguish between such back pay and the situation where an employee actually returns to their old job for a new employment spell. Given that a key variable in my estimation strategy relies on the length of a worker's term of employment, this is especially challenging. I make several sample restrictions in order to weed out observations that individuals would likely not consider to be an employment relationship in the way we typically think of them.

First, I only include an employment spell in the sample if at some point it could be considered the dominant job, defined as paying the highest wage of an individual's jobs in a given quarter.⁶ I also exclude employment spells that span fewer than three quarters.⁷ Since the data do not contain information on when in the quarter an individual was hired/separated, the entries for the first and last quarters of any employment spell will most likely understate the quarterly earnings rate (unless the individual was hired on the first day or left employment on the last day of a quarter). Thus, in order to accurately measure the earnings rate, I must observe an individual in at least one quarter other than the first or last of an employment spell.

I remove job spells with average earnings greater than \$1 million per quarter and less than \$100 per quarter, corresponding approximately to the top and bottom 1 percent of

6. This formulation allows an individual to have more than one dominant job in a given quarter. The rationale behind this definition is that I wish to include all job spells where the wage is important to the worker. The vast majority of job spells in my sample, 90.1 percent, have zero or one quarter of overlap with other job spells. Restricting the dominant job definition to only allow one dominant job at a given time does not alter the reported results.

7. The relaxation of this assumption does not appreciably alter any of the reported results.

observations. Additionally, only firms that have greater than 25 separations to employment, 25 separations to nonemployment, and 25 recruits from employment⁸ over the lifespan of the firm are considered in order to ensure there are sufficient data to estimate the relevant elasticities. The final analysis sample is approximately 132,062,000 unique individuals having 260,939,000 employment spells at 308,000 unique firms.

B. Empirical Strategy

The construction of the labor supply elasticity measures used in this study most closely represents a firm-level implementation of the methodology proposed in Manning (2003). I first describe in detail how the labor supply elasticity measures are calculated, followed by a description of how they are used to examine firms' employment behavior.

1. Dynamic measure

One possible method to estimate the labor supply elasticity facing the firm is to regress the natural log of firm size on the natural log of firm wages. However, this would effectively interpret the firm size–wage premium as evidence in favor of a monopsonistic labor market. While this could certainly be the case, a large firm size–wage premium is a well-known result in the labor economics literature often attributed to nonmonopsony related factors. For example, economies of scale may increase the productivity, and thus the marginal product, of workers at large firms. I therefore rely on estimating parameters presented in the theoretical section, which are plausibly identified, and then combine them using results from Manning (2003) and Equation 6 to produce an estimate of the labor supply elasticity to the firm.

In the prior literature, this dynamic monopsony model has typically either been estimated using data from one or a small number of firms (Ransom and Oaxaca 2010; Depew and Sorensen 2013; Depew, Norlander, and Sorensen 2017) or from aggregate measures at the economy/industry level (Manning 2003; Hirsch, Schank, and Schnabel 2010; Hirsch and Jahn 2015; Bachmann and Frings 2017; Hirsch, Jahn, and Schnabel 2018). While it is quite valuable to characterize averages accurately, much can be gained by looking at things separately by firm. First, firm-specific models are more flexible from a functional form perspective with the trade-off of heightened computational resources.⁹ Second, there may be substantial variation in the degree of market power possessed by firms, with many firms operating in markets quite different from the average. Finally, with firm-level measures of market power I am able to (i) validate that the Manning (2003) approach yields results that make sense and (ii) empirically test the relationship between market power and other important covariates. To my knowledge, only Webber (2015) and Webber (2016) estimate firm-level elasticities for a broad set of firms. The present paper has access to an additional five years of data, relative to Webber

8. I can effectively relax these sample size restrictions by pooling multiple firms together (for example, treating firms in the same geographic area with identical NAICS codes as part of the same labor market). These restrictions generally lead to slightly larger estimated elasticities (increases of roughly 0.10).

9. Some models took more than one week to run using SAS on a powerful multiprocessor server.

(2015) and Webber (2016), and thus allows for a time series analysis that these previous studies were unable to undertake.

Based on the results presented in the theoretical model section, three quantities must be estimated in order to construct the labor supply elasticity measure (ϵ_S^E , ϵ_S^N , and $w\theta^R(w)/\theta^R(w)[1 - \theta^R(w)]$), as well as the calculated shares of separations and hires to/from employment for each firm. Each of the following models are run separately for every firm in the sample (as well as on the whole sample for comparison purposes), where the unit of observation is an employment spell; thus, one individual can appear in multiple firm's models. Looking first at the separation elasticities, I model separations to nonemployment as a Cox proportional hazard model given by

$$(9) \quad \lambda^N [t | \beta^{N,sep} \log(\text{earnings})_i + X_i \gamma^{N,sep}] = \lambda_0(t) \exp [\beta_q^{N,sep} \log(\text{earnings})_i + X_i \gamma^{N,sep}]$$

where $\lambda(\cdot)$ is the hazard function, λ_0 is the baseline hazard, t is the length of employment, $\log(\text{earnings})$ is the natural log of individual i 's average quarterly earnings,¹⁰ and X is a vector of explanatory variables, including gender, race, age, education, and year control variables. While the entire sample is used, workers who transition to a new employer or who are with the same employer at the end of the data series are considered to have a censored employment spell. In this model, the parameter β_q represents a time-varying estimate of the separation elasticity to nonemployment. In an analogous setting, I model separations to employment as

$$(10) \quad \lambda^E [t | \beta^{E,sep} \log(\text{earnings})_i + X_i \gamma^{E,sep}] = \lambda_0(t) \exp [\beta_q^{E,sep} \log(\text{earnings})_i + X_i \gamma^{E,sep}]$$

with the only difference being that the sample is restricted to those workers who do not have a job transition to nonemployment. As before, β_q represents a time-varying estimate of the separation elasticity to employment. To estimate the third quantity needed for Equation 6, $w\theta^R(w)/\theta^R(w)[1 - \theta^R(w)]$, Manning (2003) shows that this is equivalent to the coefficient on log earnings when estimating the following logistic regression

$$(11) \quad P_{rec} = \frac{\exp [\beta_q^{E,rec} \log(\text{earnings})_i + X_i \gamma^{E,rec}]}{1 + \exp [\beta_q^{E,rec} \log(\text{earnings})_i + X_i \gamma^{E,rec}]}$$

where the dependent variable takes a value of one if a worker was recruited from employment and zero if they were recruited from nonemployment. To enable this coefficient to vary over time, log earnings is interacted with quarterly time dummies. The same explanatory variables used in the separation equations are used in this logistic regression. At this point, the results listed in the theoretical section can be used (along with calculating the share of recruits and separations to from/to employment) in conjunction with Equation 6 to produce an estimate of the labor supply elasticity facing each firm.¹¹

10. As mentioned above, this measure excludes the first and last quarters of a job spell. Alternative measures of earnings have also been used, such as the last observed (full) quarter of earnings, with no substantial difference in the estimated elasticities.

11. Each equation is also estimated with an indicator variable for whether the employment spell was in progress at the beginning of the data window to correct for potential bias of truncated records. Additionally, all

Given that I am interpreting the output of the above models as representative of a firm's labor market power, it is useful to think about exactly where the identifying variation comes from. In estimating the separation elasticity, a large (in absolute value) coefficient on log earnings implies that a small decrease in an individual's earnings will greatly increase the probability of separating in any given period. In a perfectly competitive economy, we would expect this coefficient to be infinitely large, as workers would be highly sensitive to wage changes. Similarly, a small coefficient implies that the employer can lower the wage rate without seeing a substantial decline in employment.

2. Analysis

A set of earnings regressions are run to assess the impact of a reduced labor supply elasticity during the recession on workers' earnings. Explicitly, I estimate :

$$(12) \quad \log(\text{quarterly earnings}_{ij}) = \beta \text{elasticity}_j + \gamma X_{ij} + \delta Y_j + \theta Z_i + \varepsilon_{ij}$$

The dependent variable is the natural log of individual i 's average quarterly earnings while working at firm j . The elasticity variable represents firm j 's estimated labor supply elasticity. X is a vector of person and firm characteristics, which may vary by the employment spell, including age, age-squared, tenure (quarters employed at firm), tenure-squared, education,¹² gender, race, ethnicity, quarter effects, indicator variables for the two-digit NAICS sector, and the size (employment) of the firm. Y is a vector of firm fixed effects, Z is a vector of person fixed effects, and ε is the error term. Time-invariant characteristics in X are excluded in models with person or firm fixed effects.

Using the firm-level sample, I model the impact of a firm's labor supply elasticity on the employment behavior of the firm across the business cycle. I estimate variations of the following equation:

$$(13) \quad \text{Rate}_{jt} = \beta \text{elasticity}_{jt} + \gamma \text{Quarter}_t + \delta \text{Elasticity}_{jt} * \text{Quarter}_t + \theta X_{jt} + \varepsilon_{jt}$$

The dependent variable represents the growth, separation, or hiring rate of firm j in quarter t . Elasticity is firm j 's labor supply elasticity, models were run using both the long-run (for example, time-invariant) and time-varying elasticity, with no differences noted in the resulting coefficients. The model also includes quarter fixed effects, quarter-by-elasticity interactions, and a set of control variables X (firm-level averages of gender, education groupings, race, ethnicity, age, industry, and employment). To ensure that extreme outliers do not influence the results, only firm's with labor supply elasticities below 5 (about 95 percent of the data) are included in the regressions.

models were reestimated using only job spells for which the entire job spell was observed, with no substantial differences observed between these models.

12. Reported educational attainment is available for only roughly 15 percent of the sample, although sophisticated imputations of education are available for the entire sample. The results presented in this paper correspond the full sample of workers (reported education and imputed education). All models were also run on the sample with no imputed data, and no substantive differences were observed. In particular, since the preferred specification includes person fixed effects, and thus educational attainment drops out of the model, this is of little concern.

V. Results

A. Summary Statistics

Table 1 reports summary statistics at both the employment spell and firm levels. Some descriptive statistics deviate modestly from typical survey-based analyses of the labor market. This is due in part to the unit of observation being a person–firm employment spell and in part to the sample restrictions described above (for example, dominant jobs, spanning at least three quarters, etc.). The average employment spell spans about ten quarters, with more than 60 percent of spells resulting from a move from another job. The quarterly nature of the LEHD data make it difficult to precisely identify¹³ whether an individual separated to employment or nonemployment, and therefore the proportion of separations to employment is slightly higher than comparable statistics reported in Manning (2003).

The average firm in my sample employs nearly 3,000 workers in a given quarter. Several qualifications must be made for these statistics. First, the distributions are highly skewed, with the median firm employing only 400. Second, these figures cannot be interpreted as point-in-time estimates, but rather totals throughout an entire quarter. Finally, a firm is defined at the state level (for example, all Walmarts in Florida), rather than at the establishment level.

B. Monopsony over the Business Cycle

Table 2 presents the labor supply elasticity estimates from a model that produces one economy-wide figure (as opposed to separate estimates for each firm). This is conceptually a good place to begin because it allows us to use distinctly different sources of identifying variation to generate the elasticities. Column 3 controls for firm-level heterogeneity and is thus a less flexible version of the firm-specific elasticities that are the focus of much of the manuscript. In this case, identification is coming from within-firm variation in wages-responsiveness. Here, an upward-sloping labor supply curve can be thought of as being generated by factors like taste/compensating differentials variation across workers or an individual-specific match component. By contrast, Column 4 leverages person-specific variation in job wages/separations, and is identified from workers moving between firms. This job-ladder setting is more akin to the Burdett and Mortensen setting of firm-wide wage policies. One concern with using this source of variation to identify wage-responsiveness is that job changes are often not exogenous, and the estimated elasticities could be biased downward if unobserved ability is positively correlated with job switches. The extent of endogenous mobility in this setting was examined extensively in Webber (2015) and found not to have any substantial

13. In order to classify a job separation as going to nonemployment, there must be no reported earnings for an entire quarter following the end of the first employment spell. This is quite conservative, as it requires there be no earnings for a period of between three and nine months (minus two days) depending on when during a quarter the separation/hire occurred. This definition was chosen because it leads to the most conservative (least monopsonistic) results, although the differences are small. I also reran all models where separations to employment/nonemployment were classified on the basis of the imputed date (based on earnings in the final quarter relative to earnings in the penultimate quarter) that a worker left the firm.

Table 1
Summary Statistics

Variable	Mean	SD
Panel A: Unit of Observation: Employment Spell		
Age	38	15.2
Female	0.5	0.5
White	0.77	0.42
Hispanic	0.14	0.34
<High school	0.14	0.34
High school diploma	0.29	0.45
Some college	0.32	0.47
College degree+	0.25	0.43
Tenure (quarters)	10.1	10.7
Log(quarterly earnings)	8.5	1
Separation rate	0.18	0.15
Hiring rate	0.17	0.14
Recruited from employment	0.64	0.48
Observations	260,939,000	
Panel B: Unit of Observation: Firm–Year–Quarter		
Firm hires per quarter	493	1592
Firm employment	2962	10772
Employment growth rate	1.01	0.15
Observations	11,137,000	

Table 2
Economy-Wide Labor Supply Elasticity Estimates

Full Sample with Basic Controls	Only Firms with an Individually Estimated Elasticity	Basic Controls and Firm Fixed Effects	Basic Controls and Individual Fixed Effects
0.76	0.82	0.83	0.86

Notes: These labor supply elasticities were obtained by estimating Equations 9–11, on a pooled sample of all (dominant) employment spells. Each model contains age, age-squared, and indicator variables for female, nonwhite, Hispanic, high school diploma, some college, college degree or greater, state-by-year, and each of 20 NAICS sectors. The second column restricts the sample to only those firms for which a firm-specific elasticity can be estimated (described in detail in Section IV). The third and fourth columns display the results when firm and individual heterogeneity are accounted for in each stage of the estimation process (for example, stratified proportional hazard models and conditional logits). For computational reasons (due mainly to the nonlinear nature of these models), a specification that controls for both firm and individual heterogeneity could not be estimated.

Table 3
Firm-Level Labor Supply Elasticities

Model	ε_R^E	ε_R^N	ε_S^E	ε_S^N	ε
Earnings only	0.42	0.1	−0.42	−0.55	0.85
Full model	0.47	0.11	−0.47	−0.62	0.96
Full model (time-varying)	0.57	0.14	−0.57	−0.75	1.17

Notes: The first row represents estimates from Equations 9–11 where the only regressor in each model is log earnings. The second row estimates the same equations and includes age, age-squared, and indicator variables for female, nonwhite, Hispanic, education category controls, and year effects. Employer controls include number of employees working at the firm and industry indicator variables. The first four columns report the average firm-level elasticities of recruitment from employment and nonemployment and the separation elasticities to employment and nonemployment, respectively. The final column combines these elasticities, along with the calculated shares of separations/recruits to/from employment, separation rates, and growth rates to obtain the labor supply elasticity. The first two rows report only the long-run elasticities, while the third row describes the elasticities when a steady state is not assumed, and they are allowed to vary over time.

impact on either the estimated labor supply elasticities or any subsequent models that use the elasticities as inputs.

Importantly, these distinct sources of variation (observationally similar workers within the same firm vs. the same worker at different firms) yield nearly identical estimates of the labor supply elasticity to the firm and imply a highly noncompetitive labor market. The remainder of the paper presents results from models estimated separately by firm, though the economy-wide analogues (when possible to estimate) are nearly identical.

Tables 3 and 4 present information about the elasticities estimated through Equations 9–11. The results are broadly similar to Webber (2015) and Webber (2016) (there are fewer states included in this paper’s sample, and observations are over a more recent time horizon). The first four columns of Table 3 report the average firm-level elasticities of recruitment from employment and nonemployment and the separation elasticities to employment and nonemployment, respectively. The final column combines these elasticities, along with the calculated shares of separations and recruits to and from employment to obtain the labor supply elasticity. The first three rows report only the long-run elasticities, while the final row describes the elasticities when each quantity is allowed to vary over time. The recruitment and separation elasticities are each of the expected sign and relative magnitude (for example, the elasticity of separations to employment is smaller than its nonemployment counterpart). Depending on the specification, I estimate a mean (worker-weighted) labor supply elasticity of between 0.85 and 1.17, with the latter estimate corresponding to the richest model specification.¹⁴

14. Due to the large sample size of the data, standard errors are too small to be of any meaning in the full sample. A standard error of less than 0.01, for instance, has no practical significance when evaluating whether the average firm operates in a monopsonistic or competitive environment. The exception to this is Figure 1, where I present changes in estimated labor elasticities over time. Here, the estimates are slightly less precise, and smaller changes may be economically meaningful; hence, a 95 percent confidence interval is presented.

Table 4
Distribution of Estimated Firm-Level Labor Supply Elasticities

Mean	Percentiles				
	10th	25th	50th	75th	90th
1.17	0.26	0.5	0.85	1.35	2.13

Notes: Three separate regressions, corresponding to Equations 9–11, were estimated separately for each firm in the data that met the conditions described in the data section. The coefficients on log earnings in each regression were combined, weighted by the share of recruits and separations to employment, separation rates, and growth rates according to Equation 6 to obtain the estimate of the labor supply elasticity to the firm. Demographic and human capital controls include age, age-squared, and indicator variables for gender, ethnicity, racial status, and education level. Employer controls include number of employees working at the firm and industry indicator variables. Year effects are included in all models.

The results presented in Table 3 suggest that the typical firm operates in a highly monopsonistic/noncompetitive labor market. Although this study cannot pinpoint the specific causes, it is clear that workers are far less mobile than the model of a perfectly competitive labor market would imply. Webber (2015) and Rinz (2022) both find that reduced labor market competition is most pronounced and harmful to low income workers. This may be explained in part by recent work highlighting the surprisingly high number of noncompete agreements used by firms in industries that employ many such workers (Krueger and Ashenfelter 2022). It is worth noting that risk aversion or non-economic factors, such as the relationship with one's supervisor, could lead to this same relationship between low income workers and mobility. The closer you are to the financial cliff, the less willing you will be to switch jobs for a small wage gain while risking job security.

As shown in Table 4, there is significant dispersion in the distribution of labor supply elasticities faced by firms. The top 10 percent of firms operate in markets with elasticities greater than 2.13, and the top five percent of firms face elasticities greater than 5. The assumption of a perfectly competitive market is likely a good approximation for these firms. Conversely, the majority of firms (median labor supply elasticity = 0.85) compete for workers in labor markets where the typical employee is highly unlikely to move in response to small or even modest changes in their wage. This gives these firms considerable latitude to pay lower wages without worrying about a mass exodus of employees.

Figure 1 plots the labor supply elasticity between 1998 and 2012 for the states included in my sample. During the late 1990s and early 2000s, the labor supply elasticity to the firm fluctuated mostly between 1.15 and 1.20, with a pre-recession peak in late 2005. The financial crisis in 2008 produced a clear and prolonged downturn in the labor supply elasticity facing the firm, with the low point coming in 2010 Quarter 4 at 1.01.

But what does this mean in terms of worker welfare? Theoretically, a decline in the labor supply elasticity from 1.20 to 1.01 leads to earnings losses of 8.7 percent.¹⁵ To test

15. Based on the profit-maximizing condition $w = \frac{pQ'(L)}{1+\varepsilon}$ where w represents the wage, the numerator is the marginal product of labor, and ε is the elasticity.

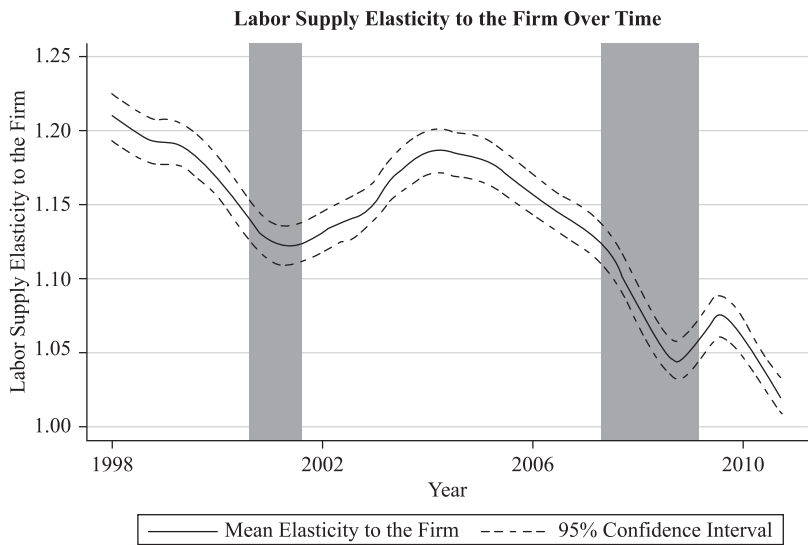


Figure 1
The Labor Supply Elasticity to the Firm over Time

the empirical impact of this decline, Table 5 presents a series of earnings regressions to assess the impact of a change in the labor supply elasticity. The model with the most detailed controls (person and firm fixed effects) suggests that the decline of the labor supply elasticity from 1.20 to 1.01 led to earnings losses of 3.8 percentage points. It should be noted that this is likely a lower bound on the relationship between market power and wages, as each firm-level elasticity is (i) measured with error and (ii) a weighted average of many different worker-specific elasticities (thus introducing more measurement error).¹⁶ It should also be noted that there is good reason to believe that the decline in the estimated labor supply elasticity during the Great Recession may have been underestimated for another reason. Mass layoffs often disproportionately involve the workers with the shortest tenure. From the standpoint of the estimation strategy, these short-tenure, low-wage workers will appear to be behaving in a very responsive way (that is, how workers would behave in a perfectly competitive market when they have a low wage).

The persistent decline in the labor supply elasticity firms face provides important context for the overall health of the economy. Researchers have more often focused on

16. I attempt to mitigate the impact of measurement error in several ways. First, the sample restrictions described in the data section lead to firm-level hazard models with substantially more precise results. Second, I ran all models only including firms that had a precisely estimated elasticity and noted a small increase in the estimated parameters in Table 5. Third, I combined data for firms with identical NAICS codes in close geographic proximity in order to increase the sample sizes of the estimating equations, and again I only noted a small increase in the Table 5 parameters. On the basis of this evidence, my belief (though untestable) is that measurement error that arises from workers within the same firm competing in dramatically different labor markets is more important than estimation error in any attenuation bias that may be present. This is also supported by the results of Webber (2016), who looked at gender-specific labor supply elasticities.

Table 5
Impact of Search Frictions on Earnings

Coefficient on labor supply elasticity	0.14	0.12	0.08	0.05	0.05	0.06	0.20
Demographic controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Employer controls	No	No	Yes	Yes	Yes	Yes	Yes
Tenure controls	No	No	No	Yes	Yes	Yes	Yes
State fixed effects	No	No	No	No	Yes	Yes	Yes
Person fixed effects	No	No	No	No	No	Yes	Yes
Firm fixed effects	No	No	No	No	No	No	Yes
R-squared	0.005	0.238	0.312	0.331	0.338	0.784	0.95

Notes: A pooled national sample of all dominant employment spells subject to the sample restriction described in the data section is used in this set of regressions. The dependent variable is the natural log of quarterly earnings. Demographic controls include age, age-squared, and indicator variables for gender, ethnicity, racial status, and education level. Employer controls include the number of employees working at the firm and industry indicator variables. Tenure controls include the length (in quarters) of the employment spell, as well as its squared term. Year effects are included in all models. These results are unweighted, but all models were also estimated with demographic weights constructed by the author. There were no significant differences between the weighted and unweighted models. Standard errors are not reported because the *t*-statistics range from 500 to 1000, but they are available upon request along with all other estimated coefficients. There are 267,310,000 observations in each specification.

decreasing competition in the product market, as when evaluating consumer welfare or the decline in the labor share of income (Autor et al. 2017; De Loecker, Eeckout, and Unger 2020). While beyond the scope of this paper, future work should attempt to examine the factors driving this decline in labor market competitiveness, as Figure 1 makes clear that it is driven by more than pure business cycle factors. Identifying whether the decline is due to increased labor market concentration, declining unionization, changes in worker preferences or ability to move, or even spillovers from increased product market power can lead to dramatically different policy proposals for how to increase the level of competition in the labor market.

Table 6 shows the differential change in the labor supply elasticity facing the firm across various industries. The table reports the labor supply elasticity at its peak and trough for each North American Industry Classification System (NAICS) sector. Professional/scientific/technical services experienced the greatest (percentage) decline (24 percent). On the other end of the spectrum, accommodation/food services saw relatively mild declines in competition (4 percent), although this industry began from a much lower base. One interesting note from Table 6 is that health care/social service workers are employed in one of the least competitive labor markets, validating the intuition of the many economists who studied this sector in search of evidence of monopsonistic wage-setting policies (Hurd 1973; Link and Landon 1975; Link and Settle 1979; Adamache and Sloan 1982; Feldman and Scheffler 1982; Sullivan 1989; Hirsch and Schumacher 1995; Matsudaira 2014).

Figure 2 plots the (smoothed) predicted quarterly growth rates for firms at the median and 90th percentile of the labor supply elasticity distribution. These predicted values are obtained by estimating Equation 13 and using the interactions between the year-quarter

Table 6
Mean Labor Supply Elasticity by NAICS Sector

NAICS Sector	Mean Labor Supply Elasticity 2005 Quarter 1	Mean Labor Supply Elasticity 2010 Quarter 4
Agriculture	1.31	1.10
Mining/oil/natural gas	1.60	1.28
Utilities	1.40	1.22
Construction	1.59	1.27
Manufacturing	1.72	1.40
Wholesale trade	1.52	1.26
Resale trade	1.07	0.95
Transportation	1.45	1.20
Information	1.22	0.98
Finance and insurance	1.38	1.12
Real estate and rental	1.13	0.94
Profession/scientific/technical services	1.30	0.98
Management of companies	1.00	0.87
Administrative support	0.97	0.86
Educational services	0.96	0.85
Health care and social assistance	0.87	0.75
Arts and entertainment	0.93	0.75
Accommodation and food services	0.96	0.89
Other services	1.19	1.00
Public administration	1.11	0.96

Notes: The numbers in this table represent averages by NAICS sector of the estimated labor supply elasticity to the firm. Three separate regressions, corresponding to Equations 9–11, were estimated separately for each firm in the data that met the conditions described in the data section. The coefficients on log earnings in each regression were combined, weighted by the share of recruits and separations to employment, separation rates, and growth rates according to Equation 6 to obtain the estimate of the labor supply elasticity to the firm. Demographic and human capital controls include age, age-squared, and indicator variables for gender, ethnicity, racial status, and education level. Employer controls include number of employees working at the firm. Year effects are included in all models.

fixed effects and the labor supply elasticity. Prior to the financial crisis, the growth rate for the (monopsonistic) median firm was consistently below that of more competitive firms, staying relatively close to one, and thus not expanding or contracting. However, during the Great Recession there is a convergence of the growth rates between monopsonistic and competitive firms, with the growth rate of monopsonistic firms exceeding that of their more competitive counterparts at some points. The rates are not statistically distinguishable from one another after the onset of the Great Recession in late 2007.

Figures 3 and 4 plot the predicted hiring and separation rates for the median and 90th percentile firms in the labor supply elasticity distribution. These figures show that the convergence in growth rates between monopsonistic and competitive firms is primarily

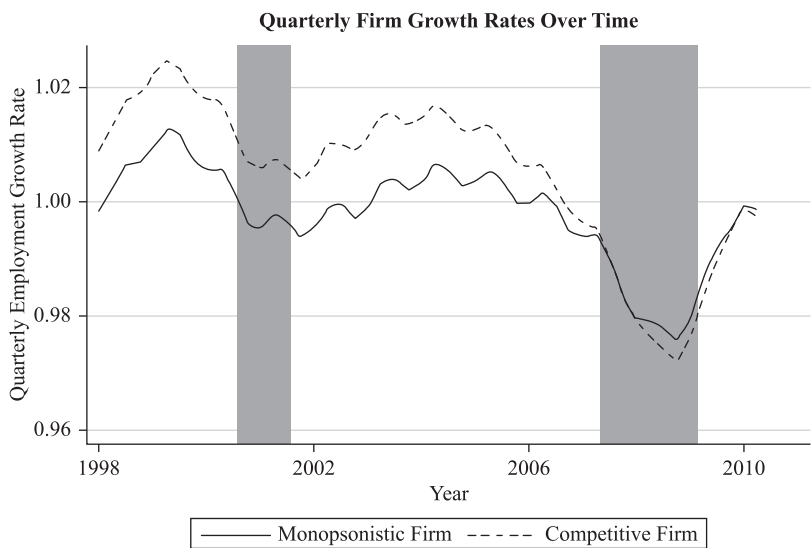


Figure 2
Competitive and Monopsonistic Quarterly Growth Rates

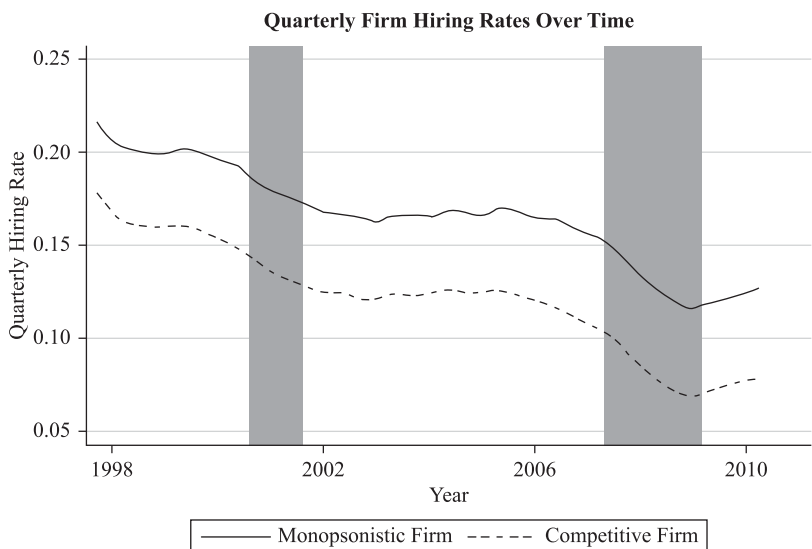


Figure 3
Competitive and Monopsonistic Quarterly Hiring Rates

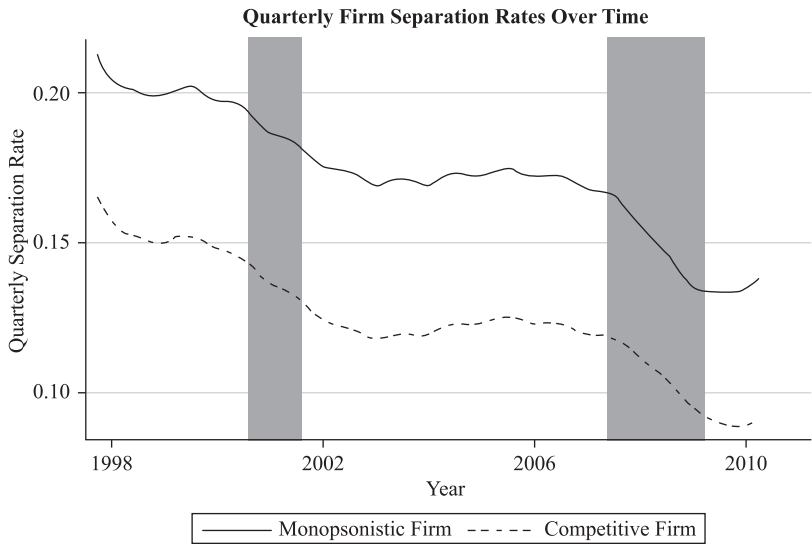


Figure 4
Competitive and Monopsonistic Quarterly Separation Rates

due to changes in the relative separation rates. Over the period from 1998 Quarter 1 to 2008 Quarter 3, the disparity in hiring rates between the median and 90th percentile firm is 0.0275, and from 2008 Quarter 4 onward it increased to 0.030. However, the separation rate differential in the period prior to the financial crisis is 0.0313, while the differential in the latter period decreased to 0.0263. This leads to a growth rate differential of 0.0046 in the period prior to the financial crisis, and a growth rate differential of -0.0015 after the financial crisis. Intuitively, these results imply that during the (mostly) strong economic times in the decade prior to the financial crisis, firms facing a relatively competitive supply curve grew about 0.46 percent in employment more per quarter than the median firm, which faces a monopsonistic supply curve. However, in the period after the financial crisis hit, monopsonistic firms had a higher (or less negative) growth rate than their more competitive counterparts.

Taken together this evidence points to the conclusion that firms facing relatively monopsonistic labor supply curves attempt to smooth their employment to a greater degree than firms in relatively more competitive markets. While not testable with the currently available data, this is consistent with a model where training or other adjustment costs have an important interaction with the degree of competition in the labor market in relation to firm behavior. In strong economic times, monopsonistic firms have lower employment than competitive firms, which is predicted by the neoclassical monopsony model (analogous to a monopoly, which produces a lower output than a perfectly competitive firm). However, in bad economic times, the monopsonist would prefer to keep employment relatively constant and is able to do so because of their increased market power. The intuition behind this desire is that firms would rather not

bear significant adjustment costs if they believe that the downturn is transitory. This finding conforms with the predictions of the Rogerson and Shimer (2011) model.

VI. Conclusion

This study finds evidence that the degree of competition in the labor market declined markedly over the first decade of the new century, at considerable cost to worker welfare. Using data from the Longitudinal Employer Household Dynamics (LEHD) infrastructure, I estimate a dynamic model of the labor market and obtain firm-level labor supply elasticities that cover approximately 75 percent of private/nonfarm employment in the United States. I find that the average (worker-weighted) labor supply elasticity facing the firm dropped from a peak of 1.20 to a low point of 1.01 in the fourth quarter of 2010. My results suggest that this decline led to earnings losses of approximately 3.8 percent. I also find heterogeneity across industries in the decline of the labor supply elasticity, with scientific/technical services seeing the largest drop in worker mobility during the Great Recession.

I find evidence that the existence of frictions in the economy may lead to fewer fluctuations in the employment behavior of firms. Relatively monopsonistic firms appear to smooth their employment, growing at a lower rate than relatively competitive firms in strong economic climates but having a higher growth rate in bad economic climates.

I view the methodology and results of this paper as a complement, rather than a substitute, to other recent monopsony work. Research such as Dube, Naidu, and Suri (2020) is very credibly identified, but applies to a narrow labor market where it is not clear how generalizable the results are to the broader economy. Papers such as Azar, Marinescu, and Steinbaum (2022) and Rinz (2022) have the benefits of applying to a broad labor market and also having a clearly defined/easily understandable source of monopsony power (geographic concentration). This is also a drawback, however, as there are many potential frictions that restrict mobility that are unrelated to concentration. By contrast, the above results need make no assumptions about the source of frictions or the boundaries of a labor market, but the identification does not come from a quasi-experimental source. While no single study in this literature is perfect, the fact that such varying methodologies and frameworks all point to the same conclusion—a highly frictional labor market that has a tangible impact on the average worker—is very convincing.

The sustained decline in labor market competitiveness should be a serious concern to economists and policymakers. There are three broad classes of policies that can be used to improve outcomes for workers on this front: (i) programs that enhance worker mobility, (ii) programs that improve worker bargaining power within a firm, and (iii) antitrust intervention. The first class of policies is likely to be less controversial across the political spectrum. This could include easing or eliminating many occupational licensing requirements, prohibiting noncompete clauses in employment contracts, or decoupling major benefits such as health insurance from employment relationships. Solutions of the second type, increasing worker bargaining power, are both more traditional and politically contentious. Such policies would include raising the minimum wage and reducing barriers to unionization.

While antitrust enforcement has historically focused on imperfect competition in the product market, it seems natural that it could play a role in addressing monopsony power

that arises from certain types of frictions.¹⁷ Geographic concentration resulting from mergers or acquisitions or overly broad noncompete clauses seem good candidates for this category. The vastly different policy responses on the table underscore the need for future work in this literature to focus on identifying the specific drivers of monopsony power, as the effectiveness of each policy depends critically on the source of frictions.

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17. The role of antitrust enforcement is discussed in detail in Naidu and Posner (2022).

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