Employment Adjustment Over the Business Cycle: The Impact of Competition in the Labor Market

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Employment Adjustment Over the Business Cycle: The Impact of Competition in the Labor Market

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Abstract

Using linked employer-employee data which 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 by approximately 0.19 log points (1.20 to 1.01) since the late 1990's, with the steepest declines occurring during the financial crisis. I find that this decline in labor market competition cost workers about 4 percent in lost earnings.

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 which suggest that frictions in the economy may actually reduce employment fluctuations.

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1 Introduction

The severe labor market downturn experienced during the Great Recession was the worst seen by the U.S. in seventy years. At its peak, the national unemployment rate was 10.6 percent. The average duration of unemployment reached 35 weeks, and nearly 1 in 6 workers lost their job (Farber, 2011). Labor market churn, an important ingredient to a dynamic labor market declined markedly over this period (Lazear and Spletzer, 2012). Each of these factors implies that the competition between firms for a given worker's services declined substantially during the Great Recession. For many who lost their jobs, firms were competing with reservation wages (i.e. unemployment insurance) rather than with the wages of other firms.

Recent research (Hirsch et al., 2010; Ransom and Oaxaca, 2010; Depew and Sorensen, 2013; Booth, 2014; Webber, 2015; Naidu et al., 2016; Hirsch et al., 2018; Dube et al., Forthcominga) has highlighted both the prevalence and importance of frictions in the labor market which 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 (asymmetric information, moving costs, low job offer arrival rate, etc.) the conclusion that frictions exist has been consistent.

Using linked employer-employee data from the U.S. Census Bureau, this paper estimates the decline in labor market competition (as measured by the labor supply elasticity facing the firm) which workers experienced during the Great Recession, and evaluates the impact on earnings. Additionally, I examine the employment patterns of firms which compete in more versus less competitive labor markets over the past decade, and how the labor supply elasticity faced by an individual firm affects its hiring behavior.

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,

[1] A recent excellent study Hirsch et al. (2018) has examined time series variation in the labor supply elasticity of German firms.

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 about 16% 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 earnings losses 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.

I estimate that in a strong economy, firms in less competitive labor markets have lower growth rates than firms in relatively more competitive labor markets. I find that this is 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 the search model presented in Rogerson and Shimer (2011). The intuition is that when labor adjustment costs are large enough, firms would rather not lay off workers in the first place knowing that eventually they would want to hire them back. Firms in relatively more 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 2 describes the previous literature on competition in the labor market. Section 3 lays out the theoretical foundation for this study. The data and methods are described in Section 4. Section 5 presents the results, and Section 6 concludes.

2 Previous Literature

The concept of "monopsony" was first defined and explored as a model by Robinson (1933). Although the term is most often used in a labor market context, it can also refer to a firm which is the only buyer of an input. In the "dynamic monopsony" framework, developed and popularized primarily in Manning (2003), the word monopsony is more or less 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 et al., 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.

There is considerable evidence that the initial market conditions when a worker first enters the labor market have a persistent impact on wages and other labor market outcomes(Oyer, 2006, 2008; Genda and Kondo, 2010; Kahn, 2010; Maclean, 2013). The finding that entering the labor market during a recession can cause lower wages 20 years in the future is suggestive of significant search frictions and that the marginal productivity of labor is not the sole determinant of wages. Moreover, the negative long-term impact of being laid off, found in studies such as Jacobson et al. (1993), can also be viewed as evidence of an imperfectly competitive market.

Most of the theoretical work done on imperfect competition in the labor market 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 Allan Manning's seminal re-analysis of labor economics absent the assumption of perfect competition (Manning, 2003) . The new monopsony model of the labor market views a firm's market power as derived from search frictions rather than solely geographic power as in a classic monopsony model. These search frictions originate from imperfections in the labor market such as imperfect information about available jobs, worker immobility, or heterogeneous preferences.

Economists since Bunting (1962) have searched for empirical evidence of firms utilizing wage-setting power, typically through concentration ratios, the share of a labor market which a given firm employs. The most commonly examined market in the empirical monopsony literature has been that of nurses in hospitals (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). Since nurses have a highly specific form of human capital and there are many rural labor markets where hospitals are the dominant employer, there is intuitive appeal to this particular labor market when searching for evidence of monopsony power. Overall, the concentration ratio approach has yielded mixed results and no clear consensus.

More recently, 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

[2]See Mortensen (2003) or Rogerson et al. (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

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 et al., 2016; Azar et al., 2017; Dube et al., 2018, Forthcominga,F).

A number of recent papers use a dynamic approach similar to this study to estimate the average labor supply elasticity to the firm. In some cases, this is done for a single or small set of firms (Ransom and Oaxaca, 2010; Depew and Sorensen, 2013; Depew et al., 2017), and in others for broader labor markets (Manning, 2003; Hirsch et al., 2010; Hirsch and Jahn, 2015; Webber, 2015, 2016; Bachmann and Frings, 2017; Hirsch et al., 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 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 e presence

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.

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.

3 Theoretical Model

The seminal Burdett and Mortensen (1998) search model elegantly illustrates how develop a model of the economy in which employers post wages based on the wage-posting behavior of competing employers. Even assuming equal ability for all workers, wage dispersion is an equilibrium outcome as long as one assumes 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.

The Burdett and Mortensen model of equilibrium wage dispersion

Assume there are M_t 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 π = (p-w)N(w) where N(w) represents the supply of labor to the firm. Also define F(w) as 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 non-employed workers will accept w' if w'$\geqq$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:

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

$$s(w) = \delta + \lambda(1 - F(w)) \tag{2}$$

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 will collapse to the monopsony wage, which in this particular economy would be the reservation wage b. As λ tends to infinity the wage distribution will collapse to the perfectly competitive wage, the marginal product of labor p.

Note that 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.

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

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

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 (this assumption is relaxed for the analyses, but is maintained here to present the most straightforward model), we can rewrite Equation (3) as

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

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.

$$\varepsilon = \varepsilon_R - \varepsilon_S \tag{5}$$

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

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

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). $\theta^R$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)):

$$\varepsilon_R^E = \frac{-\theta^S \varepsilon_S^E}{\theta^R} \tag{7}$$

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

$$\varepsilon_R^N = \varepsilon_R^E - w\theta'^R(w)/\theta^R(w)(1-\theta^R(w)) \tag{8}$$

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 steady state, I also estimate each model using the short run-elasticity derived in Manning (2003) and by interacting each parameter with quarter fixed-effects (described below). All results are robust to each way of constructing the firm-level labor supply elasticity.

4 Data and Methodology

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 non-farm jobs. Information about the 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 Walmart in Florida and a Walmart in Georgia would be considered to be different firms. However, all Walmarts in Florida 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, also an analysis sample, is 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 2011 quarter 4[4]. These were chosen 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% of total U.S. private/non-farm employment during the span of the data.

Given that the identifying variation for the labor supply elasticities comes from job separations (including whether a workers separates to employment or non-employment), it is a potential problem that some states are not available. I could potentially 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 non-employment. To assess the importance of this restriction, I re-estimated 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.

I make several sample restrictions in order to weed out observations which individuals would likely not consider to be an employment relationship in the way we typically think of. These restrictions are necessary in large part because the earnings data are derived from tax records, and thus any payment made to an individual, no matter how small, will appear in the sample. As a consequence, there are many "job spells" which appear to last only one quarter, but are in fact one-time payments which do not conform with the general view of a job match between a firm and worker. For example, if I wrote a paid op-ed for a newspaper,

[4]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.

it would appear as if I had an employment relationship with that firm which lasted for one quarter.

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[5]. I also exclude employment spells which span fewer than three quarters.[6] . 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 which have average earnings greater than $1 million per quarter and less than $100 per quarter, corresponding approximately to the top and bottom 1 percent of observations. Additionally, only firms which have greater than 25 separations to employment, 25 separations to nonemployment, and 25 recruits from employment 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.

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.

[5]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 0 or 1 quarters 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.

[6]The relaxation of this assumption does not appreciably alter any of the reported results.

Dynamic Measure

One possible method to estimate the labor supply elasticity facing the firm would be 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 of course be the case, a large firm size-wage premium is a well known result in the labor economics literature, and is often attributed to non-monopsony related factors such as economies of scale increasing 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/a small number of firms (Ransom and Oaxaca, 2010; Depew and Sorensen, 2013; Depew et al., 2017), or aggregate measures at the economy/industry level (Manning, 2003; Hirsch et al., 2010; Hirsch and Jahn, 2015; Bachmann and Frings, 2017; Hirsch et al., 2018). While it is of course quite valuable to accurately characterize averages, there is much that can be gained by looking at things separately by firm. First, firm-specific models are far more flexible from a functional form perspective, although this comes at the cost of heightened computational resources.[7]. 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 1) validate that the Manning (2003) approach yields results which make sense, and 2) empirically test the relationship between market power and other important covariates. To my knowledge, only Webber (2015) and Webber (2016) are the only papers to estimate firm-level elasticities for a broad set of firms. It should be noted though that the reason this has not been done more in the prior literature is due to data constraints and not a lack of

[7] Some models took more than one week to run using SAS on a powerful multiprocessor server

desire on the part of other excellent authors cited above.

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

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

where $\lambda()$ is the hazard function, λ_0 is the baseline hazard, t is the length of employment, log(earnings) is the natural log of individual i's average quarterly earnings,[8] 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_t represents a time-varying estimate of the separation elasticity to nonemployment. In an analogous setting, I model separations to employment as

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

with the only difference being that the sample is restricted to those workers who do not have

[8] 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.

a job transition to nonemployment. As before, β_t 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

$$P_{rec} = \frac{\exp(\beta_t^{E,rec} log(earnings)_i + X_i\gamma^{E,rec})}{1+\exp(\beta_t^{E,rec} log(earnings)_i + X_i\gamma^{E,rec})} \tag{11}$$

where the dependent variable takes a value of 1 if a worker was recruited from employment and 0 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 employment, separation rates, and growth rates for each firm) in conjunction with equation (6) to produce an estimate of the labor supply elasticity facing each firm. [9]

Given that the 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 is coming 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 high. Similarly, a very small coefficient implies that the employer can lower the wage rate without seeing a substantial decline in employment.

One potential threat to identification relates to firms paying efficiency wages. If some firms have low rates of turnover because they are paying high wages (and taking other actions to reduce turnover which would be considered beneficial to workers), then firms which I classify as monopsonistic (and in some ways exploitative of workers) may in truth

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

be very worker-friendly. This is of greater concern in the full economy estimate of the labor supply elasticity to the firm found elsewhere in the literature than in my firm-level estimation since the models in this paper are run separately by firm. To see why, note that no cross-sectional (between firms) variation in the level of earnings is used to identify the labor supply elasticity in the models estimated in this manuscript. Moreover, this efficiency wage hypothesis is directly testable in a firm-specific elasticity setting. As discussed in the Results section, it is not supported (at least on average) in the data.

Analysis

The labor supply elasticity estimates described above are used in several analyses to examine the interaction of imperfect competition and the Great Recession.

First, 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 :

$$log(quarterly\, earnings_{ij}) = \beta elasticity_j + \gamma X_{ij} + \delta Y_j + \theta Z_i + \varepsilon_{ij} \tag{12}$$

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[10], 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.

[10]Reported educational attainment is only available for 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 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.

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

$$Rate_{jt} = \beta elasticity_{jt} + \gamma Quarter_t + \delta Elasticity_{jt} * Quarter_t + \theta X_{jt} + \varepsilon_{jt} \qquad (13)$$

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 (e.g. time-invariant) and time-varying elasticity, with no differences noted in the resulting coefficients. The model also includes quarter fixed effects, quarter*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.

5 Results

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 until of observation being a person-firm employment spell and in part to the sample restrictions described above (e.g. dominant jobs, spanning at least three quarters, etc.). The average employment spell lasts about two and a half years, with more than sixty percent of spells resulting from a move from another job. The quarterly nature of the LEHD data make it difficult to precisely identify[11] whether an individual separated to

[11] 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 lead to the most conservative (least monopsonistic) results, although the differences were small. I also re-ran all models where separations

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 3000 workers and hires almost 500 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 and hiring 75 in a given quarter. 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 (e.g. all Walmarts in Florida) rather than at the establishment level.

Monopsony over the Business Cycle

Table 2 and Table 3 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 over a slightly more recent time horizon). The first four columns of Table 2 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 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 (e.g. 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.[12]

to employment/nonemployment were classified based on the imputed date that a worker left the firm. The imputation was based solely on the earnings in the final quarter relative to the earnings in the penultimate quarter.

[12]Due to the large sample size of my data, standard errors are too small to be of any meaning in my 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 we smaller changes may be economically meaningful, hence a 95% confidence interval is presented.

The results presented in Table 2 suggest that the typical firm is operating in a highly monopsonistic/noncompetitive labor market. Although this paper cannot pinpoint the specific causes of this phenomenon, it is clear that workers are far less mobile than the model of a perfectly competitive labor market would imply. Webber (2015) and Rinz (2018) both find that reduced labor market competition is most pronounced/harmful to low income workers. This may in part be explained by recent work highlighting the surprisingly high number of non-compete agreements used by firms in industries which employ many such workers (Krueger and Ashenfelter, 2018). 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 the financial cliff, the less willing you will probably be to switch jobs for a small wage gain while risking job security.

As shown in Table 3, there is significant dispersion in the distribution of labor supply elasticities faced by firms. The top ten 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 2011 for the states included in my sample. During the late 1990's and early 2000's, 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[13]. To test the

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

empirical impact of this decline, Table 4 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 1) measured with error and 2) a weighted average of many different worker-specific elasticities (thus introducing more measurement error).

Table 5 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 5 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).

Table 6 displays results from estimating Equation (13) using the firm's growth, separation, and hiring rates as dependent variables. I present results for specifications with and without firm and demographic controls, however since many of these controls (such as industry or firm size) can be seen as "causing" a firm's monopsony power they may be considered bad controls. Therefore, in the text I only discuss the results for specifications without these potentially endogenous variables.

On average, I find that firms in more competitive labor markets have higher rates of growth, with a one unit increase in the labor supply elasticity being associated with a 0.4 percentage point increase in the growth rate. Decomposing the growth rate into hiring and separation rates, I find that this difference is driven by the separation rate. While both the hiring and separation rates are lower for monopsonistic firms, the change in the separation rate is greater for monopsonistic firms than it is for firms in more competitive markets, thus explaining the difference in growth rates.

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 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 1, 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.

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 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 .0275, and from 2008 quarter 4 onward it increased to .030. However, the separation rate differential in the period prior to the financial crisis is .0313 while the differential in the latter period decreased to .0263. This leads to a growth rate differential of .0046 in the period prior to the financial crisis, and a growth rate differential of -.0015 after the financial crisis. Intuitively, these results imply that in the (mostly) strong economic times in the decade prior to the financial crisis firms facing a relatively competitive supply curve grew about 0.46% 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 more steady (and is able to do so because of their increased market power) because they would rather not bear significant adjustment costs once the market conditions improve, conforming with the predictions of the Rogerson and Shimer (2011) model.

6 Conclusion

This study finds evidence that the degree of competition in the labor market declined considerably 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 which cover approximately 75% of private/non-farm 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 also find evidence that the existence of frictions in the economy may lead to fewer fluctuations in the employment behavior of firms. I find that relatively monopsonistic firms attempt to smooth their employment adjustment, growing at a lower rate than relatively competitive firms in strong economic climates but a higher growth rate in bad economic climates.

The sustained decline in labor market competitiveness should be a serious concern to economists and policymakers. There are two broad classes of policies which can be used to improve outcomes for workers on this front: 1) programs which enhance worker mobility, and 2) programs which improve worker bargaining power within a firm. 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 non-compete 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.

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Figure 1: The Labor Supply Elasticity to the Firm Over Time

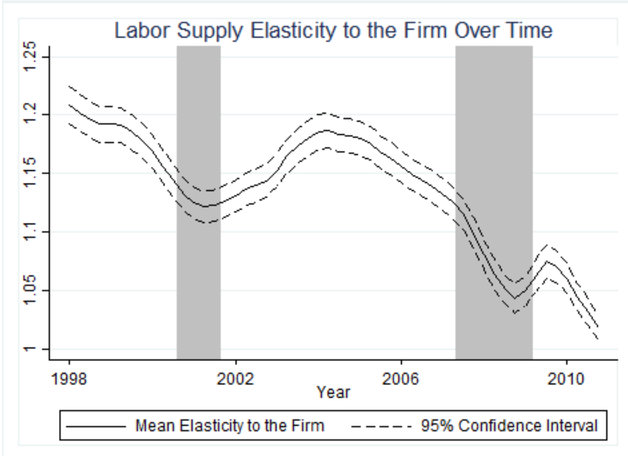

Figure 2: Competitive and Monopsonistic Quarterly Growth Rates

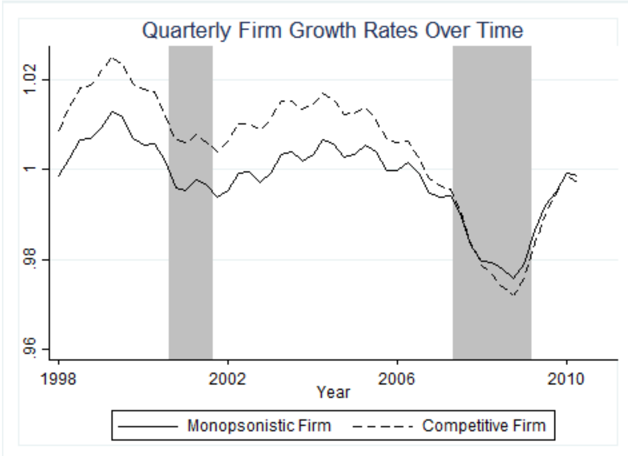

Figure 3: Competitive and Monopsonistic Quarterly Hiring Rates

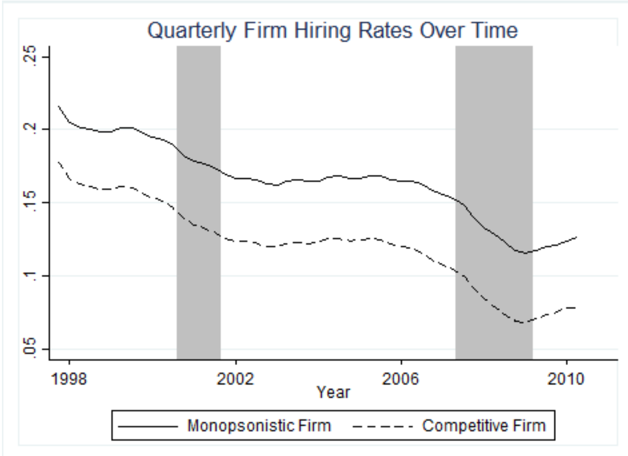

Figure 4: Competitive and Monopsonistic Quarterly Separation Rates

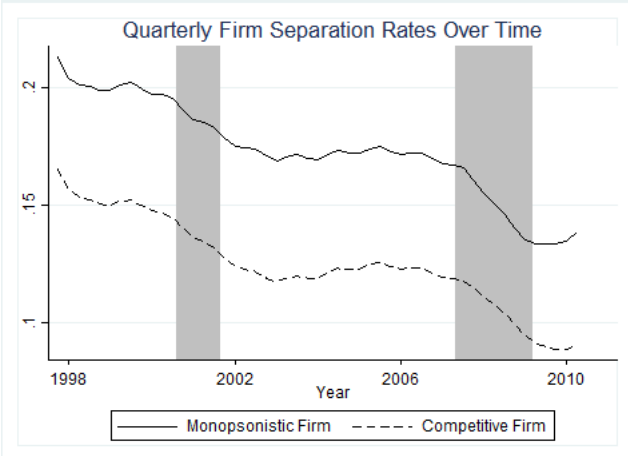

Table 1: Summary Statistics

Variable	Mean	Std Dev
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	
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: 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

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, along with 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.

Table 3: Distribution of Estimated Firm-Level Labor Supply Elasticities

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

*Three separate regressions, corresponding to equations (9)-(11), were estimated separately for each firm in the data which 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.

Table 4: 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	0.99

*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, however 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 500-1000, but are available upon request along with all other estimated coefficients. There are 267,310,000 observations in each specification.

Table 5: Mean Labor Supply Elasticity by NAICS Sector

NAICS Sector	Mean Labor Supply Elasticity 2005 Q1	Mean Labor Supply Elasticity 2010 Q4
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

*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 which 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.

Table 6: Employment Behavior and the Labor Supply Elasticity

	Growth Rate		Hiring Rate		Separation Rate	
	No Controls	Controls	No Controls	Controls	No Controls	Controls
Coefficient	.004	.005	-.022	-.013	-.025	-.016

The results represent the coefficient on labor supply elasticity when estimating Equation (13) at the firm levelboth with and without firm and demographic controls. Coefficients for each of the other elasticity and year-quarter interaction are used in calculations described in the text, and are available upon request. Approximately 11,137,000 firm-year-quarter observations are used in these models.