

Essays on Imperfect Competition in the Labor Market

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Essays on Imperfect Competition

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Abstract

This thesis examines the extent and impact of imperfect competition in the labor market (monopsony) on several important features of our modern economy. The first chapter describes in detail the justification for why monopsony is an important factor in the labor market. A dynamic model, which identifies the labor supply elasticity to the firm from job to job flows, is the basis for measuring the degree of competition faced by a firm. This chapter produces the first estimates of firm-level monopsony ever documented through the use of linked employer-employee data from the U.S. Census Bureau. The mean (worker-weighted) labor supply elasticity to the firm is estimated to be 1.08, however there is substantial heterogeneity across firms. Additionally, the model is validated through a series of earnings regressions, which conclude that a one unit increase in the labor supply elasticity is associated with an 20 percent increase in the earnings of workers. Finally, through a distributional decomposition, the impact of imperfect competition is found to be the greatest for low income workers, and that a more competitive labor market would reduce earnings inequality.

The second chapter focuses on the interaction between firm-level monopsony and the gender wage gap. This study estimates a 0.15 gap in the gender-specific labor supply elasticity averages,. This leads to an approximately 3.3 percent gap in earnings between men and women, or about 14 percent of the total gender earnings gap solely based on differences in mobility. Furthermore, the labor supply elasticity gap is almost entirely due to across firm sorting rather than within firm differentials.

The third chapter focuses on how labor market competition changes over the business cycle, in particular during the great recession. I estimate that the labor supply elasticity

to the firm declined by approximately 0.19 log points percent (1.20 to 1.01) following the financial crisis of 2008. Furthermore, this decline cost workers about 4 percent in 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 higher during poor economic climates.

Biographical Sketch

Douglas Allen Webber accepted a position as an Assistant Professor in the Temple University Department of Economics. He received his Master's and PhD from Cornell University, which he attended while funded by a National Science Foundation Graduate Research Fellowship. He holds two Bachelor's degrees from the University of Florida, one in Economics and one in Mathematics.

Doug is trained as a labor economist, and is interested in research which helps to inform public policy. His current research centers around the degree of competition in the labor market, and the impact this may have on topics such as inequality, unemployment, and the minimum wage.

Dedication

*To my wife Catherine, and my family (Stephen, Julia, Dan, and David). I owe so much to
all of you.*

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Part I

Firm Market Power and the Earnings Distribution

Abstract

Using the Longitudinal Employer Household Dynamics (LEHD) data from the United States Census Bureau, I compute firm-level measures of labor market (monopsony) power. To generate these measures, I extend the dynamic model proposed by Manning (2003) and estimate the labor supply elasticity facing each private non-farm firm in the US. While a link between monopsony power and earnings has traditionally been assumed, I provide the first direct evidence of the positive relationship between a firm's labor supply elasticity and the earnings of its workers. I also contrast the dynamic model method with the more traditional use of concentration ratios to measure a firm's labor market power. In addition, I provide several alternative measures of labor market power which account for potential threats to identification such as endogenous mobility. Finally, I construct a counterfactual earnings distribution which allows the effects of firm market power to vary across the earnings distribution.

I estimate the average firm's labor supply elasticity to be 1.08, however my findings suggest there to be significant variability in the distribution of firm market power across US firms, and that dynamic monopsony models are superior to the use of concentration ratios in evaluating a firm's labor market power. I find that a one-unit increase in the labor supply elasticity to the firm is associated with earnings gains of between 5 and 20 percent. While nontrivial, these estimates imply that firms do not fully exercise their labor market power over their workers. Furthermore, I find that the negative earnings impact of a firm's market power is strongest in the lower half of the earnings distribution, and that a one standard deviation increase in firms' labor supply elasticities reduces the variance of the earnings distribution by 9 percent.

1 Introduction

There is good reason to believe that some firms have non-trivial power in the labor market, that not all firms act as price takers and pay their employees the prevailing market wage. Intuitively, most would not switch jobs following a wage cut of one cent, and we would not expect a firm which raises wages by a small amount to suddenly have an infinite stream of workers. So it becomes an empirical question of whether the departure from perfect competition is meaningful; whether perfect competition is a good approximation for our economy, or whether a model with substantial frictions fits better.

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). For instance, Goux and Maurin (1999) conclude that on average firm effects alter an individual's wage by more than 20 percent. Furthermore, they find these firm effects are related more to firm characteristics such as size rather than productivity, implying that the firm effects are not simply absorbing workers' unmeasured marginal product of labor.

Estimating the degree of wage competition in the labor market is important for both theoretical research and policy analysis. Since perfect competition is a standard feature in many models of the labor market, evidence of significant distortions in the labor market would suggest labor economists should reevaluate the perfect competition assumption and its implications in their models. From a policy perspective, the degree of imperfect competition can drastically change the effects of institutions such as the minimum wage (Card and Krueger, 1995) or unions (Feldman and Scheffler, 1982).

While the industrial organization literature has theoretically and empirically modeled similar frictions in the product market, there has been comparatively less work done to account for distortions of the labor market. This is primarily due to the comparative lack of rich labor market data (such as linked employer-employee data) versus product market data. Most of the theoretical work done on this topic resides in the search theory literature,

with major contributions coming from Burdett and Mortensen (1998) and Shimer (2005) to name a few¹. This line of research has given rise to a "new monopsony" literature, popularized by Alan Manning's (Manning, 2003) careful analysis of labor-related topics absent the assumption of perfect competition. 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.

Even if the existence of monopsony power is accepted, estimating the degree of market power possessed by a firm is not a simple task. Economists since Bunting (1962) have searched for empirical evidence of monopsony, with the predominant method being the use of 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; Feldman and Scheffler, 1982; Hirsch and Schumacher, 1995; Link and Landon, 1975; Adamache and Sloan, 1982; Link and Settle, 1979). This market lends itself to monopsony because nurses have a highly specific form of human capital and there are many rural labor markets where hospitals are the dominant employer. Despite the relatively large literature on this narrow labor market, 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 elasticity². 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

¹See Mortensen (2003) or Rogerson et al. (2005) for a review of this literature

²The 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.

bargained pay scales and estimate a labor supply elasticity between 3 and 4. In a novel approach using German administrative data, Schmieder (2010) finds evidence of a positive sloping labor supply curve through an analysis of new establishments.

Using a dynamic approach similar to this study, Ransom and Oaxaca (2010) and Hirsch et al. (2010) both separately estimate the labor supply elasticities to the firm of men and women, each finding strong evidence of monopsonistic competition. Ransom and Oaxaca (2010) use data from a chain of grocery stores, and find labor supply elasticities of about 2.5 for men and 1.6 for women. Hirsch et al. (2010) uses administrative data from Germany to estimate elasticities ranging from 2.5-3.6 and 1.9-2.5 for men and women respectively. Applying this approach to survey data, Manning (2003) finds labor supply elasticities ranging from 0.68 in the NLSY to 1.38 in the PSID. In a developing country context, Brummund (2011) uses a novel structural production function approach, and finds strong evidence of monopsony in Indonesian labor markets, estimating labor supply elasticities between 0.6 and 1.0.

Utilizing data from the US Census Bureau's Longitudinal Employer Household Dynamics (LEHD) program, I estimate the market-level average labor supply elasticity faced by firms in the US economy, similar to the Hirsch et al. (2010) study using German data. I then extend the approach to estimate firm-level labor supply elasticities. This is accomplished through an extension to the dynamic model of labor supply proposed by Manning (2003). This method allows me to examine the effects of monopsonistic competition on the earnings distribution in great detail, and contributes to the existing literature in a number of ways. First, it is the first examination of monopsony power using comprehensive administrative data from the US. Second, my particular empirical strategy allows me to examine the distribution of monopsony power which exists in the US, and to provide the first direct evidence on the negative impact of a firm's market power on earnings. I compare the performance of the market power measures derived in this study to that of the more traditional concentration ratio to illustrate the significant contribution of the new monopsony models. Finally, I

construct a counterfactual earnings distribution in which firms' market power is reduced in order to demonstrate the impact of imperfect competition on the shape of the earnings distribution.

I estimate the average labor supply elasticity to the firm to be approximately 1.08. Estimates in this range are robust to various modeling assumptions and corrections for endogenous mobility. Furthermore, I find evidence of substantial heterogeneity in the market power possessed by firms, ranging from negligible to highly monopsonistic. While a link between monopsony power and wages has traditionally been assumed (Pigou, 1924), I provide the first direct evidence of a positive relationship between a firm's labor supply elasticity and the earnings of its workers, estimating that a one-unit increase is associated with a decrease of at least 0.09 in log earnings. I demonstrate that the effect of monopsony power is not constant across workers: unconditional quantile regressions imply that impacts are largest among low paid and negligible among high paid workers. Finally, implications in the inequality literature are addressed through the construction of a counterfactual earnings distribution, which implies that a one standard deviation increase of each firm's labor supply elasticity would decrease the variance of earnings distribution by 9 percent.

The paper is organized as follows, Section 2 describes the definition of market power utilized in this study. 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 sensitivity analyses, and Section 6 concludes.

2 Discussion of Monopsony Power

The concept of "monopsony" was first defined and explored as a model by Robinson (1933). In her seminal work, Robinson formulated the analysis which is still taught in undergraduate labor economics courses. Monopsony literally means "one buyer", and 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.

It should be pointed out that in the “new monopsony” framework, the word monopsony is synonymous with the following phrases: monopsonistic competition, imperfect competition, finite labor supply elasticity, or upward sloping labor supply curve to the firm. While the classic monopsony model is based on the idea of a single firm as the only outlet for which workers can supply labor, the new framework defines monopsony as any departure from the assumptions of perfect competition. Additionally, the degree of monopsonistic competition may vary significantly across labor markets, and even across firms within a given labor market.

In order to think about what determines a firm’s monopsony power, we must consider why we do not observe the predicted behavior from a perfectly competitive model. What gives a firm flexibility in offering a wage rather than being forced to offer the market wage? Put another way, why do we not observe workers jumping from job to job whenever they observe a higher paying opportunity for which they are qualified?

One of the most prominent reasons is that the typical worker does not have a continuous stream of job offers (this point will be discussed further in the theoretical model section). This source of monopsony power has roots in the classic monopsony framework in that, all else held constant, workers in labor markets with more firms are likely to have a greater number of offers. However, this idea takes an overly simplistic view of the boundaries of a given labor market. Most employers are likely operating in many labor markets at any given time. A prestigious university may be competing in a national or international labor market for professors, a regional labor market for its high-level administrators and technical staff, and a local labor market for the low-level service workers. Even if the arrival rate of job offers were the only source of monopsony power, it seems that geographic modeling alone would do a poor job of measuring that power. Another source of monopsony power is imperfect information about job openings (McCall, 1970; Stigler, 1962), which is not completely distinct from the arrival rate of job offers since a decrease in information can

cause a reduction in job offers. This is a particularly compelling example since studies such as Hoffer and Murphy (1992) and Polachek and Robst (1998) estimate that imperfect information about job prospects depresses wages by approximately ten percent.

The costs (both monetary and psychic) associated with changing jobs can also be thought of as giving market power to the firm. Moving costs are typically thought of as a short run cost, particularly when a worker is young. However these costs can grow significantly when a worker has a family and roots in a community. Consider the scenario of a dual-career family. Two job offers will be needed to induce either of the partners to move, a fact which gives significant bargaining power to the employers of each partner, particularly the one who is paid less. Additionally, changing jobs means that workers must adjust to a new system which will require at least a small degree of learning on the job.

Firm specific human capital also can be thought of as giving market power to the firm, since there is in effect a barrier to leaving a firm when an individual's firm specific capital is large relative to their general human capital. In fact, Wasmer (2006) concludes that markets with substantial search frictions induce workers to overinvest in firm specific human capital.

Reputation costs likely also play a large role in the mobility of workers. Potential employers would be very suspicious of hiring a worker who changes jobs the moment he is offered any wage increase. For all of these reasons, and likely many more, workers must be selective with the wage offers they choose to accept, thus leading to a labor market with substantial frictions.

As discussed in Manning (2011), another way to think about imperfect competition in the labor market is in terms of the rents received by the employee and the employer. On the worker's side, the rents to a given job match would be the difference between the current wage (utility) and the worker's opportunity cost, either a wage (utility) from a different firm or unemployment benefits. Studies such as Jacobson et al. (1993) implicitly estimate these rents by exploring the impacts of exogenous job destruction. This literature estimates wage losses of 20-30 percent, implying significant rents to employees from a given job match.

From the employer's perspective, the rents from the i th job match are the difference between $(MP_i - w_i)$ and $(MP_j - w_j)$, where j is the next worker who would be hired if worker i leaves the firm. This is a harder quantity to measure empirically, but can be approximated (assuming that the marginal product is the same for workers i and j) by hiring and training costs. The estimates of hiring and training costs as a fraction of total wages paid tend to be in the range of 3-7 percent (Oi, 1962; Abowd and Kramarz, 2003). The ratio of worker rents to employer rents can be thought of as a measure of the firm's market power. If the worker's opportunity cost is high relative to her employer's opportunity cost, then the employer will be able to extract a large amount of the surplus from the job match. However, if the converse is true, the worker will be in the position of power.

A relatively new branch of labor economics which focuses on the initial labor market conditions when a worker enters the labor market may also provide insight into the mobility of workers. A number of studies (Oyer, 2006, 2008; Genda and Kondo, 2010; Kahn, 2010) find persistent and negative wage effects from entering the labor market in a bad economy, lasting for at least 20 years. These persistent effects provide further evidence that there are significant long-run frictions in the economy.

Finally, while a worker's earnings represent an important market outcome, it is important to remember that wages make up only a part of the total "compensation" to the worker. The true quality of a job match has many dimensions, such as benefits, working conditions, and countless other compensating differentials. The interaction of monopsony with these non-wage goods should be explored in future research.

3 Theoretical Model

A central feature of perfect competition is the law of one wage, that all workers of equal ability should be paid the same market clearing wage. In an attempt to explain how wage dispersion can indeed be an equilibrium outcome, Burdett and Mortensen (1998) 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 $\pi = (p-w)N(w)$ 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 $w' \geq b$ 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:

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

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

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), and incorporates a key insight from the recent working paper by Depew and Sorensen (2011) to derive the least restrictive formula for the labor supply elasticity facing the firm currently in the literature. 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.

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

Equation (3) formalizes the definitionally true statement that a firm's employment this period is equal to the fraction of workers from last period who stay with the firm plus the number of new recruits. Noting that $N_t = \gamma N_{t-1}$ where γ is the rate of employment growth between period $t-1$ and t , we can rewrite Equation (3) as

$$N_t(w) = \frac{R_t(w)}{1 - (1 - s_t(w))^{\frac{1}{\gamma_t}}} \quad (4)$$

Taking the natural log of each side, multiplying by w , and differentiating we can write the elasticity of labor supply, ε , at time t as a function of the long-run elasticities of recruitment and separations, as well as the contemporary separation and growth rates.

$$\varepsilon_t = \varepsilon_R - \varepsilon_S \frac{s_t(w)}{\gamma_t + s_t(w) - 1} \quad (5)$$

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

way

$$\varepsilon_t = \theta^R \varepsilon_R^E + (1 - \theta^R) \varepsilon_R^N - \theta^S \varepsilon_S^E \frac{s_t^E(w)}{\gamma_t + s_t^E(w) - 1} - (1 - \theta^S) \varepsilon_S^N \frac{s_t^N(w)}{\gamma_t + s_t^N(w) - 1} \quad (6)$$

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). 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 noemployment as functions of estimable quantities.

Looking first at the elasticity of recruitment from employment, we can write the recruitment from employment function and its derivative as

$$R^E(w) = \lambda \int_0^w f(x) N(x) dx \quad (7)$$

$$\frac{\partial R^E(w)}{\partial w} = \lambda f(w) N(w) \quad (8)$$

Combining Equations (4), (7), and (8), along with the definition of an elasticity ($\varepsilon_R^E = \frac{w}{R^E(w)} \frac{\partial R^E(w)}{\partial w}$), we get:

$$\varepsilon_R^E = \frac{w \lambda f(w)}{1 + \frac{s_t^E(w)}{\gamma_t} - \frac{1}{\gamma_t}} \quad (9)$$

In dealing with the numerator, note that the the derivative of the separation to employment function, $s^E(w) = \lambda(1 - F(w))$, is

$$\frac{\partial s^E(w)}{\partial w} = -\lambda f(w) \quad (10)$$

Combining equations (9), (10), and the definition of an elasticity ($\varepsilon_s^E = \frac{w}{s^E(w)} \frac{\partial s^E(w)}{\partial w}$), we can write the elasticity of recruitment from employment as a function of estimable quantities:

$$\varepsilon_R^E = \frac{-\varepsilon_S^E s_t^E(w)}{1 + \frac{s_t^E(w)}{\gamma_t} - \frac{1}{\gamma_t}} \quad (11)$$

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

$$\varepsilon_R^N = \varepsilon_R^E - w\theta^{R^*}(w)/\theta^R(w)(1 - \theta^R(w)) \quad (12)$$

This is derived from the simple definition of θ^R , the share of total recruits which come 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 (12). The second term on the right-hand side of Equation (12) 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 separation and growth rates. To my knowledge, no other study has estimated this model before.

In an economy where the arrival rate of job offers is finite (and thus the labor supply elasticity is finite) firms are not bound by market forces to pay workers their marginal product of labor. The model presented above implies that, even in a world where all firms and individuals are identical, a decrease in the arrival rate of job offers will both lower the average wage and increase inequality. To see how a firm's labor supply elasticity affects the wage it pays, consider a profit-maximizing firm which faces the following objective function:

$$\underset{w}{Max} \Pi = pQ(L) - wL(w) \tag{13}$$

P is the price of the output produced according to the production function Q. The choice of wage w determines the labor supplied to the firm L. Taking first order conditions, substituting $\varepsilon = \frac{w}{L(w)} \frac{\partial L(w)}{\partial w}$, and solving for w yields:

$$w = \frac{pQ'(L)}{1 + \frac{1}{\varepsilon}} \tag{14}$$

The numerator in Equation (14) is simply the marginal product of labor, and ε is the labor supply elasticity faced by the firm. It is easy to see that in the case of perfect competition ($\varepsilon = \infty$) that the wage is equal to the marginal product of labor, but the wage is less than then marginal product for all $0 < \varepsilon < \infty$.

Every empirical study in the new monopsony literature attempts to estimate the labor supply elasticity to the firm at the market level. In other words, they measure the (firm-size weighted) average slope of each firm’s supply curve in the market. In a highly competitive market we would expect these elasticities to be very large numbers. Among the contributions of this paper is to separately estimate each firm’s labor supply elasticity rather than a market average.

4 Data and Methodology

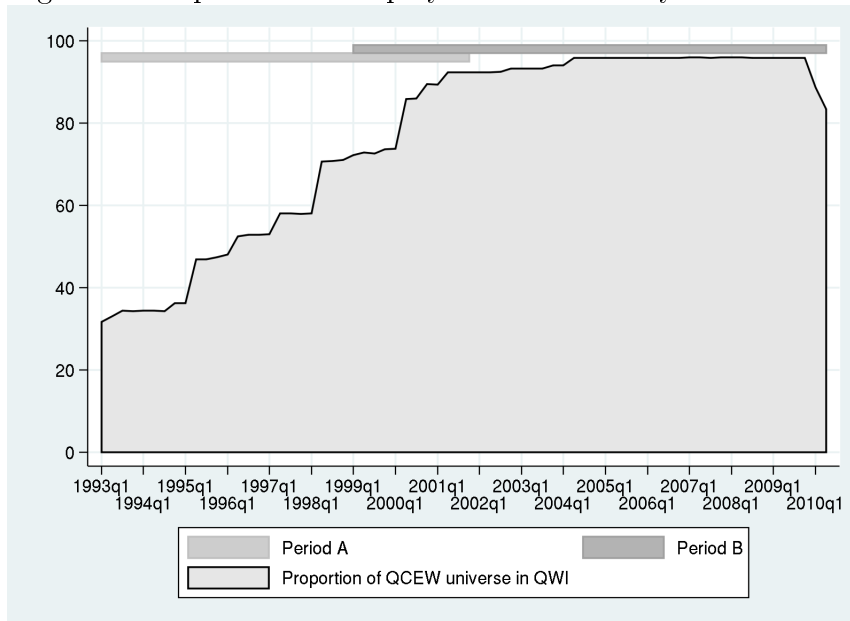
Data

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).

My sample consists of quarterly observations on earnings and employment for 47 states between 1985 and 2008³. I make several sample restrictions in an attempt to obtain the most economically meaningful results. 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.

Figure 1: Proportion of Employment Covered by the LEHD Infrastructure



Reproduced with permission from Abowd and Vilhuber (2011)

³The states not in the sample are Connecticut, Massachusetts, and New Hampshire. Not all states are in the LEHD infrastructure for the entire time-frame, but once a state enters it is in the sample for all subsequent periods. Figure 1.1 presents the coverage level of the US economy reproduced from Abowd and Vilhuber (2011).

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 quarter⁴. I also remove all spells which span fewer than three quarters.⁵ This sample restriction is related to the construction of the earnings variable. 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 almost certainly underestimate 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 get an accurate measurement of 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, which corresponds approximately to the top and bottom 1 percent of observations

Additionally, I limit the analysis to firms with 100 total employment spells of any length over the lifespan of the firm. For the full-economy monopsony model, these sample restrictions yield a final sample of approximately 149,710,000 unique individuals who had 325,630,000 total employment spells at 670,000 different firms. Additionally, for analyses using the firm-level measure of the labor supply elasticity, only firms which have greater than 25 separations to employment, 25 separations to unemployment, and 25 recruits from employment over the lifespan of the firm are considered. This reduces the analysis sample to approximately 121,190,000 unique individuals having 267,310,000 employment spells at 340,000 unique firms.

⁴This 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, 89.9 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.

⁵The relaxation of this assumption does not appreciably alter any of the reported results.

Empirical Strategy

The primary reason for the small empirical literature on monopsony is a lack of high quality data. In order to identify a firm's market power, the researcher must have a credible firm-level instrument for each firm studied or detailed employer-employee linked data to identify worker flows. I employ the latter approach in this study since finding a credible instrument for nearly every firm in the US is unlikely. The construction of the market power measures most closely represents an augmented firm-level implementation of the methodology proposed in Manning (2003).

I first describe in detail how the market power measures are calculated, followed by a description of how they are used to examine the US earnings distribution.

Location-Based Measures

I construct an overall measure of the percent of the industry-specific labor market that each firm employs (Number of workers at firm i /number of workers in firm i 's county and in firm i 's industry) using North American Industry Classification System (NAICS) industry definitions. While this variable is far from a perfect measure of an employer's power to set wages, it has several advantages over the dynamic measures to be used later in the paper. Both the construction of these measures and the regression estimates using them are transparent. Endogeneity, misspecified equations, etc. are of less concern in the construction of these labor concentration measures, and the interpretation of the regression coefficients on these variables is straightforward. This analysis corresponds to the traditional concentration ratio approach of analyzing labor market power.

Dynamic Measure

The simplest way to estimate the labor supply elasticity to the firm would be to regress the natural log of firm size on the natural log of firm wages. However, even when controlling for

various demographic characteristics, this is deemed to produce a potentially biased estimate⁶. 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.

To my knowledge, only Hirsch et al. (2010) has used a similar, but considerably more restrictive, method with administrative data which yielded an economy-wide estimate of the average labor supply curve facing the firm. Manning (2003) also estimates an economy-wide measure of the degree of monopsony using surveys such as the National Longitudinal Survey of Youth (NLSY) 1979. One of the major contributions of this paper is that I estimate the labor supply elasticities for each firm, rather than the average over the whole economy. Additionally, these prior studies imposed a steady-state assumption on their model, which the model in this paper does not impose. Estimating the labor supply elasticities at the firm level does have several advantages. First, the estimation of each of the elasticity components is much more flexible than even the least constrained specifications of Hirsch et al. (2010). Second, I will be able to use the measures as an explanatory variable, and can test a number of different models. Finally, I will be able to examine the effect of market power on earnings at each point in the market power distribution, rather than examining only the average effect. This is particularly important because theory predicts significant nonlinear effects relating to the labor supply elasticity and a firm's ability to mark down wages (Pigou, 1924). However, this strategy has the drawback that I am unable to estimate the relevant parameters, and thus the labor supply elasticity, for the smallest firms (sample restrictions are discussed in the data section).

According to the results presented in the theoretical model section, three quantities must be estimated in order to construct the labor supply elasticity measure, $(\varepsilon_S^E, \varepsilon_S^N$ and $w\theta^{R'}(w)/\theta^R(w)(1 - \theta^R(w))$), as well as the calculated separation and growth rates for each

⁶The 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

firm. Each of the following models will be 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

$$\lambda^N(t|\beta^{N,sep}\log(earnings)_i + X_i\gamma^{N,sep}) = \lambda_0(t) \exp(\beta^{N,sep}\log(earnings)_i + X_i\gamma^{N,sep}) \quad (15)$$

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,⁷ and X is a vector of explanatory variables including gender, race, age, education, and year control variables (industry controls are also included in the full-economy model). While the entire sample will be 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 represents an estimate of the separation elasticity to nonemployment. In an analogous setting, I model separations to employment as

$$\lambda^E(t|\beta^{E,sep}\log(earnings)_i + X_i\gamma^{E,sep}) = \lambda_0(t) \exp(\beta^{E,sep}\log(earnings)_i + X_i\gamma^{E,sep}) \quad (16)$$

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 represents an 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

⁷As 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.

$$P_{rec} = \frac{\exp(\beta^{E,rec} \log(\text{earnings})_i + X_i \gamma^{E,rec})}{1 + \exp(\beta^{E,rec} \log(\text{earnings})_i + X_i \gamma^{E,rec})} \quad (17)$$

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 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.⁸

To provide some intuition on the models being estimated, consider the analysis of separations to employment. A large (in absolute value) coefficient on the log earnings variable 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 concern with this procedure is that this measure of monopsony power is actually proxying for high-wage firms, reflecting an efficiency wage view of the economy where firms pay a wage considerably above the market wage in exchange for lower turnover. This is much more of a 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. The logic behind this difference is that in the full economy model cross-sectional variation in the level of earnings is used to identify the labor supply elasticity. In a firm-specific model, however, the labor supply elasticity of firm A does not mechanically depend on the level of earnings at firm B. This efficiency wage hypothesis will

⁸Each 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 directly tested.

Analysis

In addition to the full-economy models of monopsony, I include the concentration ratio and firm-level labor supply elasticity measures in earnings regressions. This provides direct evidence of the effect of firm market power on earnings, a feature not possible in the full-economy models. Additionally, it serves as a test of the efficiency wage hypothesis, which predicts that firms with low estimated labor supply elasticities will pay the highest wages. The main focus of this paper is on this model, explicitly written as:

$$\log(\text{quarterly earnings}_{ij}) = \beta \text{marketpower}_j + \gamma X_{ij} + \delta Y_j + \theta Z_i + \varepsilon_{ij} \quad (18)$$

The dependent variable is the natural log of individual i 's quarterly earnings in employment spell j . The market power variable represents firm j 's estimated labor supply elasticity or the share of the local working population employed at the firm. 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, education⁹, gender, race, ethnicity, year 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.

Finally, to examine whether there is a disproportionate impact of imperfect competition on workers near the bottom of the earnings distribution, I construct a counterfactual earnings distributions in which each firm's labor supply elasticity is increased. The counterfactual

⁹Reported educational attainment is only available for about 15 percent of the sample, although sophisticated imputations of education are available for the entire sample. The results presented in this paper correspond to 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.

distribution is constructed according to the unconditional quantile approach decomposition suggested in Firpo et al. (2011). Unconditional quantile regression, first introduced in Firpo et al. (2009), estimates the parameters of a regression model as they relate to the quantiles of the dependent variable. This contrasts with traditional quantile regression, which estimates parameters corresponding to the conditional (on the included regressors) quantiles of the dependent variable. The unconditional quantile approach is most advantageous in models with relatively low R-squared (i.e. all wage regressions) since the quantiles of y are most likely to diverge from the quantiles of \hat{y} (predicted dependent variable) in this scenario.

Under this approach, unconditional quantile regressions are performed on every 5th quantile of the earnings distribution using the same model as Equation (18). The estimated coefficients on the labor supply elasticity variable from each regression will then be used to simulate the impact of a one unit increase in the labor supply elasticity to the firm on earnings in the associated quantile.

5 Results

Summary Statistics

Table 1.1 reports both employment spell and firm-level summary statistics. Since the unit of observation is the employment spell rather than the individual, and only dominant jobs are included, some statistics deviate slightly from typical observational studies of the labor market (such as a nearly even split of job spells between men and women). 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 identify¹⁰ whether an individual separated to employment or nonem-

¹⁰The definition used in this paper requires an individual to have no reported earnings for an entire quarter following an employment spell to be defined as a separation to nonemployment, with all other separations coded as a separation to employment. This definition was chosen because it lead to the most conservative (least monopsonistic) results, although the differences were small. The other methods tried involved imputing the time during the quarter at which employment stopped/started based on a comparison of the earnings reported in the last/first quarter to a quarter in which I know the individual worked the entire quarter.

ployment, and therefore the proportion of separations to employment is slightly higher than comparable statistics reported in Manning (2003).

Table 1.1: 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
Firm Concentration	0.01	0.02
Separation Rate	0.15	0.13
Recruited from Employment	0.64	0.48
Observations	267,310,000	
Unit of Observation: Firm		
Firm Industry-Concentration	0.09	0.16
Firm Hires per Quarter	493	1592
Firm Employment	2962	10772
Employment Growth Rate	1.01	0.15
Observations	340,000	

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 is that statistics are not point in time estimates, but rather totals throughout an entire quarter. Finally, remember that these are at the firm (state-level) rather than at the establishment (individual unit) level. Also of note are the employment concentration ratios, with the average firm employing roughly 9 percent of their county's industry specific labor force.

Location-Based Measure

As previously noted, many studies have attempted to search for evidence of monopsony in the labor market through the use of concentration ratios. While this approach was the best available given prior data constraints, it assumes that monopsony power is derived only from geographical constraints.

Table 1.2 presents the estimated impact of a ten percentage point increase in the concentration ratio in various specifications of Equation (18). These results suggest that, in general, a firm's geographic dominance does not appear to significantly alter the wage bill it pays. Note that when the models are run separately by North American Industry Classification System (NAICS) sector, as depicted in Table 1.3, there is evidence that firms with high concentration ratios in certain industries (such as the utilities sector) pay slightly lower wage bills. However, the effect sizes are small relative to the observed distribution of concentration ratios. Given the small results, and the fact that the industry-specific effects seem to be centered around zero, it seems plausible to conclude that geographic constraints in the labor market play at most a small role in wage determination for the average worker.

Impact of a ten percentage point increase in concentration ratio on log(earnings)	0.0213	0.0053	0.0109	0.0066	0.0114
Demographic and human capital controls	No	Yes	Yes	Yes	Yes
Employer controls	No	No	Yes	Yes	Yes
Tenure Controls	No	No	No	Yes	Yes
State fixed-effects	No	No	No	No	Yes
R-Squared	0.0013	0.2369	0.3300	0.3438	0.3502
Observations	325,630,000	325,630,000	325,630,000	325,630,000	325,630,000

*A pooled national sample of all dominant employment spells is used in this set of regressions. The dependent variable is the natural log of quarterly earnings. Demographic and human capital controls include: age, age-squared, and indicator variables for gender, ethnicity, racial status, and education level. Employer controls include indicator variables for each of the 20 NAICS sectors and number of employees working at the firm. Tenure controls include the length (in quarters) of the employment spell, as well as its squared term. Year effects are included in all models. Standard errors are not reported because all t-statistics are greater than 50. Observation counts are rounded to the nearest 10,000 for confidentiality reasons.

Full-Economy Model

I first compute the average labor supply elasticity to the firm prevailing in the economy by estimating Equations (15)-(17) on a pooled sample of all (dominant) employment spells, and combining the results according to Equation (6). Table 1.4 presents the output of a several specifications of the full-economy monopsony model. The estimated elasticities range from 0.76 to 0.82 depending on the specification.¹¹ These elasticities are certainly on the small side, implying that at the average firm a wage cut of one percent would only reduce employment by .8 percent. However, this magnitude is still within the range observed by Manning (2003) in the NLSY79. Additionally, even the inclusion of fixed-effects still puts many more restrictions on the parameter estimates than separate estimations for each firm. Based on a comparison of the full-economy model and the firm-level model presented in the

¹¹i.e. The inclusion of random effects and the use of a conditional logit model to account for person or firm effects as in Hirsch et al. (2010)

next section, the failure to fully saturate the full economy model likely produces downward biased estimates. A detailed discussion of factors which may attenuate these estimates, as well as structural reasons we should expect these results from US data, is given in the “Discussion and Extensions” section.

Table 1.3: Concentration Ratio Regressions by NAICS Sector	
Industry	Impact of a ten percentage point increase in concentration ratio on log earnings
Agriculture	0.0055
Mining/Oil/Natural Gas	0.0071
Utilities	-0.0760
Construction	-0.0157
Manufacturing	0.0050
Wholesale Trade	-0.0142
Resale Trade	-0.0009
Transportation	0.0361
Information	-0.0308
Finance and Insurance	-0.015
Real Estate and Rental	0.022
Profession/Scientific/Technical Services	0.019
Management of Companies	0.056
Administrative Support	-0.01
Educational Services	-0.005
Health Care and Social Assistance	0.016
Arts and Entertainment	0.046
Accommodation and Food Services	0.021
Other Services	-0.129
Public Administration	-0.013

*A pooled national sample of all dominant employment spells is used in this set of regressions. The dependent variable is the natural log of quarterly earnings. Demographic and human capital 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. Tenure controls include the length (in quarters) of the employment spell, as well as its squared term. Year effects are included in all models.

Full sample	Full sample with firm FE	Only firms with an individually estimated elasticity
.76	.82	.81

*These labor supply elasticities were obtained by estimating equations (15)-(17), on a pooled sample of all (dominant) employment spells. Each model contained age, age-squared, along with indicator variables for female, nonwhite, Hispanic, high school diploma, some college, college degree or greater, year, and each of 20 NAICS sectors.

Firm-Level Measure

Table 1.5 presents the elasticities estimated through Equations (15)-(17). 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 to obtain the labor supply elasticity. Of note is that the labor supply elasticity does not appear to depend substantially on the regressors included in the model. 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. Not accounting for the time-varying nature of the labor supply elasticity, as has been common in the prior literature, appears to underestimate its magnitude by 20%.

Model	ε_R^E	ε_R^N	ε_S^E	ε_S^N	ε
Earnings Only	0.41	0.1	-0.41	-0.5	0.84
No Education Controls	0.43	0.3	-0.43	-0.52	0.89
Full Model	0.47	0.46	-0.47	-0.54	0.95
Full Model (Time-Varying)	0.6	0.59	-0.6	-0.67	1.08

The first row represents estimates from equations (15)-(17) 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, and year effects. Employer controls include number of employees working at the firm and industry indicator variables. The third row adds indicator variables for completing a high school diploma, some college, and college degree or greater. 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 three rows report only the long-run elasticities, while the fourth row describes the elasticities when a steady-state is not assumed, and they are allowed to vary over time.

Table 1.6 displays information about the distribution of firms' labor supply elasticities, and Figure 1.2 presents a kernel density plot of the market power measure¹². This distribution is constructed by separately estimating Equations (15)-(17) for each firm. While the median supply elasticity (0.75) is close to the estimate from the full-economy model, there appears to be significant variation in the market power possessed by firms. I estimate a mean labor supply elasticity of 1.08, however, there are many firms (about 3 percent of the sample) with labor supply elasticities greater than 5. It appears that while there is a nontrivial fraction of firms whose behavior approximates a highly competitive labor market, the majority of the distribution is characterized by significant frictions. While not surprising, to my knowledge this is the first documentation of the large discrepancy in firms' ability to set the wage.

¹²For confidentiality reasons, the long right tail of the kernel density plot has been suppressed

Table 1.6: Distribution of Estimated Firm-Level Labor Supply Elasticities					
	Percentiles				
Mean	10th	25th	50th	75th	90th
1.08	0.22	0.44	0.75	1.13	1.73

*Three separate regressions, corresponding to equations (15)-(17), 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.

Figure 1.2: Distribution of Labor Supply Elasticities

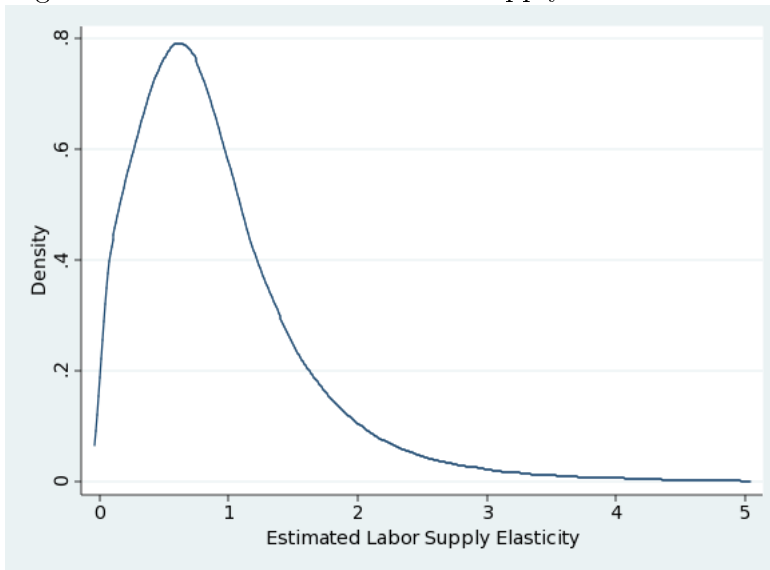


Table 1.7 reports average labor supply elasticities broken down by NAICS sector. I find significant variation in these estimates across industries. The manufacturing sector appears to enjoy the least wage-setting power, with a labor supply elasticity of 1.82. As manufacturing is likely the most heavily unionized of all sectors, this result is not surprising. By contrast, firms in the health care (0.78) and administrative support (0.72) sectors seem to wield the greatest wage-setting power. This is consistent with the focus on the healthcare market among economists investigating monopsony power.

Table 1.7: Mean Labor Supply Elasticity by NAICS Sector	
NAICS Sector	Mean Labor Supply Elasticity
Agriculture	1.43
Mining/Oil/Natural Gas	1.52
Utilities	1.18
Construction	1.42
Manufacturing	1.82
Wholesale Trade	1.48
Resale Trade	1.03
Transportation	1.47
Information	1.17
Finance and Insurance	1.27
Real Estate and Rental	1.01
Profession/Scientific/Technical	1.17
Services	
Management of Companies	1.17
Administrative Support	0.72
Educational Services	0.91
Health Care and Social Assistance	0.78
Arts and Entertainment	0.94
Accommodation and Food Services	0.85
Other Services	1.04
Public Administration	1.19

*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 (15)-(17), 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.

The central focus of this paper is presented in Table 1.8, which estimates various specifications of Equation (18) in order to measure the impact of market power on the earnings distribution. Unconditionally, a one unit increase in the labor supply elasticity increases earnings by .13 log points. Even the specifications with the most detailed controls estimate a strong positive relationship between a firm's labor supply elasticity and the earnings of its

workers. These estimates range from an impact of 0.05 log points in the model with person fixed-effects to an impact of 0.9 log points (or 10 percent after applying the formula $\exp(\beta)$) with a full complement of firm effects¹³. This is an important result for the new monopsony literature, because it rules out the possibility that the dynamic model identification strategy is actually identifying high-wage firms whose employees do not often switch jobs due to the high wages.

There is good reason to believe that the estimates in Table 1.8 are lower bounds of the true impact of firm market power on earnings. Each labor supply elasticity is a weighted average of many more precisely defined elasticities which would more accurately measure a firm's market power over a particular individual. For example, firms likely face different supply elasticities for every occupation, and potentially different elasticities across race and gender groups. From a measurement error perspective, regressing the log of earnings on the average labor supply elasticity to the firm would attenuate the estimates relative to the ideal scenario where I could separately identify every occupation specific elasticity.

¹³All models were also run using the time-invariant long run labor supply elasticity rather than the time varying measure. The results of each model which could be run using this measure (firm effects could not be included) were nearly identical.

	0.13	0.11	0.05	0.03	0.03	0.05	0.09
Coefficient on labor supply elasticity							
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	No
Firm fixed-effects	No	No	No	No	No	No	Yes
R-Squared	0.005	0.238	0.312	0.331	0.338	0.784	0.90

*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.

While these results are clear evidence that firms exercise their market power, there is reason to believe that firms are not using the majority of labor market power available to them. Bronfenbrenner (1956) first made this point, arguing that most firms in our economy likely faced upward sloping labor supply curves but that these firms would not pay substantially less than the competitive wage. This could be because firm's choose to maximize some function of profits and other quantities such as public perception and worker happiness.

To test this assertion, we can calculate what the coefficient on labor supply elasticity should be in an economy where firms only maximize profits and the mean labor supply elasticity is 1.08. This is done by taking the derivative of the coefficient on the marginal

product of labor in Equation (14) and dividing this by the coefficient itself, a formula which simplifies to $\frac{1}{\varepsilon^2 + \varepsilon}$. Evaluating this at a labor supply elasticity of 1.08 implies that if firms were exploiting all of their market power then the markdown from the marginal product of labor implied by the coefficient on labor supply elasticity in Table 1.8 should be about 0.45, much greater than the estimated effect. Even assuming a high degree of measurement error in the assignment of the average labor supply elasticity to all workers in a firm would likely not account for this disparity. One possibility is that firms reduce labor costs through other avenues than wages which are more easily manipulated such as benefits. Alternatively, this may be evidence that firms do not solely maximize profits, but instead maximize some combination of profits and other quantities (i.e. public perception).

Also of note in Table 1.8 is how the coefficient on the gender-specific labor supply elasticity variable changes as person and firm fixed effects are added. The noticeable increase in the coefficient, both when firm and person effects are added to the model, imply that on average low-wage firms have higher labor supply elasticities, and low-wage workers have higher labor supply elasticities. This is in line with the current thinking regarding monopsony power and its interaction with skilled and unskilled labor (Stevens, 1994; Muehleman et al., 2010).

Counterfactual Distribution

Table 1.9 details the disproportionate effect which firms' market power has on workers at the low end of the earnings distribution. Assuming a one unit increase in the labor supply elasticity for each firm (approximately 1 standard deviation), the 10th percentile of the earnings distribution increases by 0.09 log points under the counterfactual assumption, while the median worker sees an increase of 0.04 log points and the 90th percentile remains unchanged. The nonlinear impacts are also clearly seen in the unconditional quantile regression coefficients, which are 4-5 times greater than the OLS coefficient at lower quantiles and essentially zero at the upper end of the distribution.

Table 1.9: Counterfactual Distribution Analysis					
Change (log points) in Quantiles of the Earnings Distribution					
Quantile	10th	25th	50th	75th	90th
Change in log(earnings)	0.09	0.05	0.04	0.01	0.00
Inequality measure	Variance	90-10	50-10	90-50	
Earnings distribution	.94	1.32	1.18	1.12	
Counterfactual distribution	.86	1.30	1.16	1.11	

*The counterfactual distribution was constructed by estimating unconditional quantile regressions at every fifth quantile of the earnings distribution, and using the supply elasticity coefficient from each regression to simulate the effect at each quantile of a one-unit increase of the labor supply elasticity. Demographic and human capital 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.

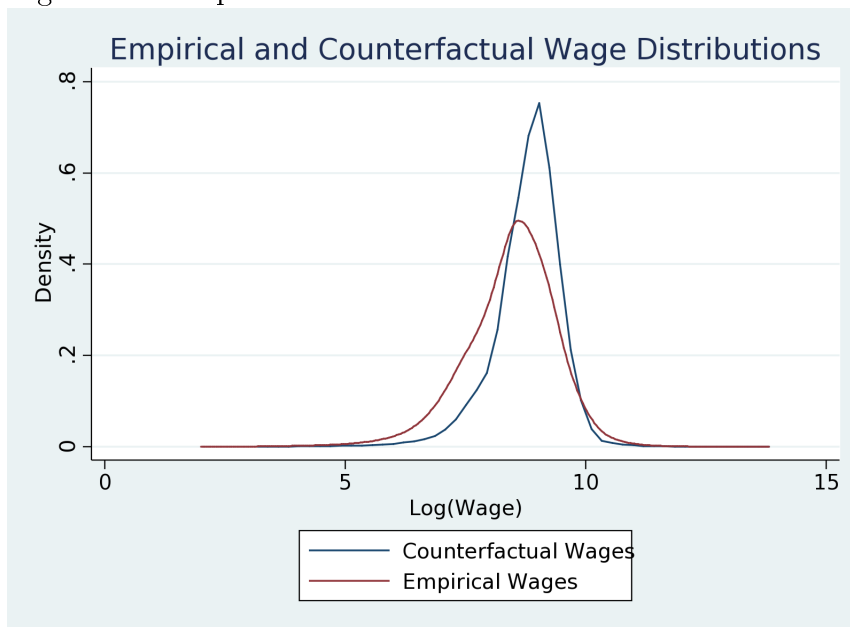
Standard measures of inequality are also reported in Table 1.9 for both the empirical and counterfactual distributions. A one unit increase in firms' labor supply elasticity is associated with a 9 percent reduction in the variance of the earnings distribution (0.94 to 0.86 log points). Similarly, we see decreases in the 90-10 ratio (1.32 to 1.3), 50-10 ratio (1.18 to 1.16), and 90-50 ratio (1.12 to 1.11).

These results could arise from a number of different scenarios, the examination of which is beyond the scope of the current paper. It may reflect low-ability workers having few outside options for employment. This could be due to strict mobility constraints, a less effective job referral network (Ioannides and Loury, 2004), lower job search "ability" (Black, 1981), or simply being qualified for fewer jobs. Another mechanism through which a firm's market power might differentially affect low wage workers is gender discrimination, as suggested by Hirsch et al. (2010) or racial discrimination. These questions deserve a much deeper treatment, and should be explored in future research.

Figure 1.3 plots both the empirical earnings distribution and the counterfactual distribu-

tion under a more drastic assumption which more closely approximates perfect competition, that each firm's labor supply elasticity is increased by a factor of 10 (median elasticity goes from .74 to 7.4). The variance of the counterfactual distribution is considerably lower, with nearly all of the movement occurring in the lower half of the distribution. The striking fact about Figure 1.3 is that the Burdett and Mortensen model predicts this same behavior as the arrival rate of job offers increases.

Figure 1.3: Empirical and Counterfactual Distributions



It is important to note that the results in the counterfactual distribution are estimated from a model which includes all person and firm controls, but no person or firm fixed effects. This is because identifying off of within person/firm variation in a sense redefines the unconditional quantiles of the distribution, and can introduce substantial bias into the results. Given that the OLS estimates of the impact of firm market power are larger in the specifications which include fixed effects, the results in Table 1.9 should be taken as lower bounds.

Discussion and Extensions

The labor supply elasticities reported in this paper imply that firms possess a high degree of power in setting the wage. For a variety of reasons, these elasticities are on the lower end of those present in the literature. In this section I address the factors which contribute to these results.

First, it should be noted that the only other studies to estimate the labor supply elasticity to the firm with comprehensive administrative data used European data. Given the very restrictive (from the point of view of the employer) employment laws in place in many European countries, this result is not surprising. Assuming that job security accrues over time within firm but drops following a transition to a new firm, any law which makes it more difficult to fire a worker effectively lowers the cost to the employee of switching jobs because job security is less of a factor.

One potential criticism of the labor supply elasticities derived in this paper is that the data do not contain detailed occupation characteristics. This problem is mitigated by the fact that the measures are constructed at the firm level in that I am only comparing workers in the same firm in the construction of a firm's monopsony power. Additionally, previous studies such as Hirsch et al. (2010) and Manning (2003) find that the addition of individual-level variables had little impact on the estimated labor supply elasticities and that it was the addition of firm characteristics which altered the results. As a further check of this problem, I compute the aggregate monopsony measures in the NLSY, as done in Manning (2003), both with and without detailed occupation characteristics. As shown in Table 1.10, I find that the difference between these labor supply elasticities is about 0.2 and is not statistically significant. Keep in mind that even if this difference were statistically significant, the estimates in this paper are still a long way from implying perfect competition. Thus, I conclude that the absence of occupation controls in the LEHD data will not seriously bias the results of this study. Additionally, the firm-level analyses performed in this paper were estimated at the occupation level on a small subset of the LEHD data which does include

occupation codes. The resulting labor supply elasticity distribution is quite similar to the firm-level elasticity distribution.

Table 1.10: Robustness Checks

*Panel A: NLSY comparisons	With versus without occupational effects	Full history versus partial history	
Bootstrapped difference in labor supply elasticity	0.20	-.46	
Std Error	0.14	.76	
**Panel B: Endogenous mobility corrections	Uncorrected labor supply elasticity	Earnings of job changers adjusted downward	Control for Heckman selection correction
Median of distribution	.75	.74	.76
*Panel A: Equations (15)-(17) were estimated on a sample of employment spells from the NLSY79 from 1979-1996 (the last year for which detailed information on recruitment and separation dates are available). The specifications include the same variables available through the LEHD data: age, age-squared, year effects, along with gender, ethnicity, race, industry, and education indicators. The first column compares the labor supply elasticities with and without the inclusion of occupational fixed effects. The second column compares the labor supply elasticities with and without the assumption that only the last third of every individual's work history is known.			
**Panel B: The second column represents a recalculation of the labor supply elasticity in which workers who are recruited away from another job have their earnings adjusted downward by the average premium of moving from job n to job n+1. The third column represents a recalculation of the labor supply elasticity in which the inverse Mills ratio of a Heckman selection model for mobility is controlled for in each of Equations (15)-(17). The omitted category in the Heckman model is the number of new local jobs in each workers current industry.			

A potentially more serious problem in the estimation of the labor supply elasticity to the firm is endogenous mobility. Consider the standard search theory model with on the job search: A worker will leave their current job if they receive a higher wage offer from another firm. Their wage at the new firm is then endogenously determined since in effect it was drawn from a distribution truncated at the wage of the their previous job. In this sense, the earnings data for those individuals who were hired away from another job is biased upward,

which will bias estimates of the labor supply elasticity to the firm downward. I deal with the endogenous mobility bias in several different ways. First, I estimate the average earnings premium an individual gets from moving to their n th job (where n is the job number in a string of consecutive employment spells). For instance, workers' earnings increase on average .19 log points when they move from their first to their second jobs. I then reduce the earnings of all job movers by the average premium associated with a move from job $n-1$ to n . For example, all workers in their second jobs of a string of employment spells would have their earnings reduced by .19 log points.¹⁴ The rationale behind this adjustment is that I only observe workers moving from one job to another if they receive a higher wage offer (This is a typical assumption of on-the-job search models, and is overwhelmingly true in the data). Thus, the earnings I observe in the second job are endogenously determined, since they were in a sense drawn from a strictly positive offer distribution.

Second, I recalculate the labor supply elasticities with a Heckman selection correction. In this model I define the selected group as those who separate from one job to another, and use the number of new jobs in an individual's state and industry as the excluded variable. The logic behind this restriction is that the state-industry specific labor market should be highly correlated with the likelihood that an individual moves to a new job, but should be uncorrelated with that individual's unobserved "ability" to move. The inverse Mills ratio from the Heckman selection model is included as a regressor in each of the Equations (15)-(17). As noted in Table 1.10, each of these corrections leads to a trivial change in the labor supply elasticity distribution.

One final concern regarding endogenous mobility is that we do not observe the complete history of workers, only that within the time-frame of the LEHD infrastructure. Thus, any employment spells in progress at the beginning of our window which are the result of a hire from another firm may introduce bias into the results. To assess the degree to which

¹⁴Define a string of employment spells as consecutive jobs an individual holds with no time spent outside the labor force. In other words, each job transition in a string of employment spells is defined as being a separation to, or recruitment from, employment. An observation takes a default value of 1, 2 if the employment spell is the second in a string of spells, etc.

this is a problem, I again employ the NLSY79. I use a Monte Carlo approach to compare the estimated labor supply elasticities using the complete worker histories and using only employment spells which occurred in the final third of the sample window. This is the ideal comparison, where the first calculation takes into account the entire work histories of each individual and the second calculation uses only those spells observed after an arbitrary date. The Monte Carlo analysis finds that using the complete worker histories leads to a statistically insignificant decrease of the estimated labor supply elasticity. This implies that the use of some partial histories in this study is not likely a problem, and at worst yields an underestimate of monopsony power.

For the reasons mentioned in this section and probably many others, critics may claim that this paper does not accurately estimate the labor supply elasticity to the firm, and they could be right. As with any identification strategy, this study relies on assumptions, not all of which are testable. But while the average firm's labor supply elasticity may not be exactly 1.08, the variable which I call a supply elasticity is certainly some kind of weighted average highly correlated with mobility and individuals' responsiveness to changes in earnings. The fact that this measure is highly correlated with earnings, especially for those at the bottom of the distribution, tells us that our economy is less competitive than we commonly assume.

6 Conclusion

This study finds evidence of significant frictions in the US labor market, although the severity of these frictions varies greatly between labor markets. I estimate the average firm's labor supply elasticity to be quite monopsonistic at 1.08, however there is a nontrivial fraction of firms who do appear to be operating in an approximately competitive labor market. While identifying the precise frictions which contribute to firms' labor market power is beyond the scope of this study, I can conclude that a firm's geographical dominance alone does not account for all or even most of their ability to affect the wage offer distribution.

I extend the dynamic model-based empirical strategy proposed by Manning (2003) to identify firm level labor supply elasticities. The use of these measures of firm market power in earnings regressions provides the first direct test of the validity of the new monopsony model. I find that a one unit increase in a firm's labor supply elasticity is associated with at least a 10 percent increase in earnings on average. Further exploring the earnings distribution, I find highly nonlinear effects implying that the negative effects of monopsony power are concentrated at the lower end of the distribution. While these effects are certainly not trivial, it is important to note that there is evidence that firms only utilize a fraction of their market power.

The development of the firm-level measures of labor market power described in this paper could have a significant impact on how we view the interaction of imperfect competition with traditional models of the labor market. Future research will examine topics such as gender/race wage gaps, minimum wage laws, unionization, labor demand over the business cycle, agglomeration, and many others.

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Part II

Firm-Level Monopsony and the Gender Pay Gap

Abstract

This study uses linked employer-employee data to estimate the labor supply elasticity facing the firm, separately by gender, for a comprehensive sample of U.S. firms. Using a dynamic model of labor supply, which identifies the labor supply elasticity to the firm off of job to job transitions, I find evidence of substantial search frictions in the economy, with females facing a higher level of frictions than males. However, the majority of the gender gap in labor supply elasticities is driven by across firm sorting rather than within firm differences, a feature predicted by the Bowlus (1997) equilibrium search model, but which has not been previously documented. On average, I find that males face a labor supply elasticity 0.15 points higher than females, a differential which leads to 2.0% lower earnings for women (or about 9% of the adjusted gender earnings gap). However, this is slightly less than half of the theoretically implied impact which the previous literature has been forced to rely upon.

1 Introduction

The male-female wage gap has long been a fixture of the labor economics literature (see Altonji and Blank (1999), Blau and Kahn (2008), or Bertrand (2011) for excellent summaries). While certainly not true of all studies, an abundance of the literature evaluates factors which contribute to the gap by (1) estimating wage equations controlling for all observable characteristics between men and women, (2) adjusting for differences in the observables through a decomposition method, and (3) interpreting all or some of the remaining gap as discrimination or some other unobservable factor. The interaction between the model coefficients and the group level differences in each observable variable is taken to be the contribution of that variable to the wage gap. This is a perfectly reasonable strategy, and in effect is exactly what this study does.

The difference between this study and the previous literature is the ability to control for detailed firm-level measures of labor market power. An assumption of most of the literature, dating back to Becker (1971), is that the structural features of the labor market are the same for both men and women. By this I mean that if we could perfectly control for all ability-related personal characteristics then two workers at the same firm doing the same job must be paid the same wage, and if not then the residual difference is due to discrimination. Becker's analysis is underlied by the belief that the perfectly competitive market forces would drive discriminating employers out of the labor market in the long run.

Recent evidence refutes these assumptions, finding significant frictions in the labor market Manning (2003); Webber (2012), as well as theoretical Bowlus (1997) and empirical (Ransom and Oaxaca, 2010; Hirsch et al., 2010) evidence that these frictions may differ by gender. This implies that firm characteristics may play a large role in wage determination, and that firm fixed-effects would not be enough to explain the effect of these frictions on the wage gap. Additionally, it implies that part of the wage gap might be explainable through firms' profit maximization; in other words, price discrimination rather than taste discrimination.

Using the Longitudinal Employer Household Dynamics (LEHD) infrastructure, linked

employer-employee data from the US Census Bureau, I separately estimate the labor supply elasticities for men and women at nearly 100,000 firms spanning 47 states. This strategy allows me to evaluate two distinct avenues through which firm market power may contribute to the male-female wage gap, within firm and across firm disparities in the gender specific labor supply elasticities. To understand the difference, consider an economy where the male labor supply elasticity is greater (more competitive) than the female labor supply elasticity by the same magnitude at every firm. Now consider a parallel economy with the same aggregate difference in gender specific labor supply elasticities, but instead of each firm having the same differential there is no difference in the elasticities at any firm but instead women disproportionately work at firms with low labor supply elasticities.

In both economies the market-level labor supply elasticities for men and women and the implied impact of market power on the wage gap are the same, but the mechanisms are quite different. In the first economy women face less competition for their labor (potential mechanisms will be discussed later), a fact which is exploited by firms in the form of lower wages for equally qualified workers. In the second economy, each firm pays its workers the same wage rate regardless of gender, with the difference in market-level wages arising from segmentation of the labor force, with male-dominated firms operating in more competitive labor markets than multi-sex firms. Note in this second economy traditional discrimination is still very possible, but it operates through the employment margin rather than the wage margin.

Using a dynamic labor supply model to separately estimate male and female labor supply elasticities for each firm in my sample, I find strong evidence of across-firm labor supply elasticity differentials, but only small within-firm differentials. At firms where I am able to estimate both a male and female elasticity, I find average (worker-weighted) labor supply elasticities of 0.98 and 0.94 for men and women respectively. However, the average labor supply elasticities are 1.09 and 0.94 for men and women respectively when I examine firms for which I can estimate at least one of the gender-specific elasticities. Furthermore, I can

directly estimate the impact of the gender gap in search frictions on the male-female earnings gap. I estimate that on average gender-specific search frictions lead to 2.0% lower earnings for women relative to men.

This paper contributes to the current literature in several important ways. First, the previous literature has only been able to examine how labor supply elasticities differ by gender at the market level. Thus, this literature can only produce two market-level elasticities (one male and one female), whereas the current paper produces firm-specific elasticities for more than one hundred thousand firms. This allows me to characterize the distribution and composition of the gender labor supply elasticity gap (within versus across firm, industry, etc.). Second, when evaluating the impact of imperfect competition on the gender wage gap, the previous literature has been forced to provide a theoretically implied impact (because two market-level elasticities cannot be used in statistical inference) rather than a directly estimated impact as is done in this study. I find that the theoretically implied impact drastically overstates the directly estimated impact. Finally, the model used in this study is considerably more flexible than the gender pay gap models which have previously been estimated, allowing for substantially more firm heterogeneity as well as allowing the labor supply elasticity to vary over time.

The paper is organized as follows, Section 2 describes motivation behind looking at the gender wage gap through a monopsony perspective. Section 3 discusses the previous literature. Section 4 lays out the theoretical foundation for this study. The data and methods are described in Section 5. Section 6 presents the results and sensitivity analyses, and Section 7 concludes.

2 Monopsony and the Gender Pay Gap

The concept of “monopsony” was first defined and explored as a model by Robinson (1933). In her seminal work, Robinson formulated the analysis which is still taught in undergraduate

labor courses. Monopsony literally means “one buyer”, and 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.

It should be pointed out that in the “new monopsony” framework, the word monopsony is synonymous with the following phrases: monopsonistic competition, oligopsony, imperfect competition, finite labor supply elasticity, or upward sloping labor supply curve to the firm. While the classic monopsony model is based on the idea of a single firm as the only outlet for which workers can supply labor, the new framework defines monopsony as any departure from the assumptions of perfect competition. Additionally, the degree of monopsonistic competition may vary significantly across labor markets, and even across firms within a given labor market.

Webber (2012) discusses in detail some of the many potential sources of a firm’s monopsony power, including: geographic constraints, moving costs, firm specific human capital, job security, asymmetric information, compensating differentials, and more. In this study, I will focus instead on factors which may cause a difference in the labor supply elasticities for men and women.

Many of the factors which may cause a difference in the male and female labor supply elasticities are sociological in nature. For example, on average the male’s job within a marriage is the dominant job. So a family may make locational decisions based primarily on the job prospects for the husband, thus forcing the wife to search for a job only in a local labor market centered around her husband’s place of employment. Women may also place a greater importance on non-wage benefits offered by employers, such as flexible work schedules or other family-friendly practices which limit the number of jobs which are suitable. For instance, if female workers are more risk averse, in terms of either job or earnings stability, than their male counterparts, then this may act as a compensating differential which would manifest itself in the form of a lower labor supply elasticity (Bonin et al., 2007). Additionally, since the core cause of a firm’s monopsony power lies in the fact that workers do not have an infinite stream of job offers, discrimination in the hiring process against women would lead to

a lower labor supply elasticity (and thus lower wages) even for women at nondiscriminating firms because they would have fewer outside options. This is an important point which is explored within the context of an equilibrium search model in Black (1995).

Much of the recent labor literature views monopsony power through a search theory context, a framework which has also been used to model gender wage differentials. Bowlus (1997) extends the standard on the job search model to allow for an individual to occupy one of three states (employment, unemployment, and nonparticipation), and allows the underlying search parameters to vary by gender. A structural estimation of this model using the National Longitudinal Survey of Youth (NLSY) in 1979 concludes that the search behavior of men and women is statistically different, with women facing a lower arrival rate of job offers and having a higher separation rate than men. Bowlus (1997) finds that this difference in search behavior explains between 20 and 30 percent of the gender wage gap. Furthermore, Bowlus (1997) concludes that this differential would likely manifest itself through firm segmentation by gender rather, with women more likely to work in low wage firms due to the difference in search behavior rather than within-firm differences in pay.

3 Previous Literature

The empirical monopsony literature dates back to Bunting (1962), with the predominant method being the use of concentration ratios, the share of a labor market which a given firm employs. The most commonly examined market in this literature has been that of nurses in rural hospitals (Hurd, 1973; Feldman and Scheffler, 1982; Hirsch and Schumacher, 1995; Link and Landon, 1975; Adamache and Sloan, 1982; Link and Settle, 1979). This market lends itself to monopsony because nurses have a highly specific form of human capital and there are many rural labor markets where hospitals are the dominant employer. Despite the relatively large literature on this narrow labor market, 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 elasticity¹⁵. Studying the market for nurses, Sullivan (1989) finds evidence of monopsony using a semistructural 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. In a novel approach using German administrative data, Schmieder (2010) finds evidence of a positive sloping labor supply curve through an analysis of new establishments.

Manning (2003) formalized a method for identifying the labor supply elasticity facing the firm off of job to job transitions. This dynamic model of labor supply, which derives its roots from Card and Krueger (1995) and the Burdett and Mortensen (1998) equilibrium search model, is the basis for the model used in this paper. Applying the model to survey data, Manning (2003) finds labor supply elasticities ranging from 0.68 in the NLSY to 1.38 in the PSID. In a developing country context, Brummund (2011) uses a novel structural production function approach, and finds strong evidence of monopsony in Indonesian labor markets, estimating labor supply elasticities between 0.6 and 1.0.

A dynamic model of labor supply approach has also been used to evaluate the link between monopsony and the gender pay gap. Two careful studies, Ransom and Oaxaca (2010) and Hirsch et al. (2010) both separately estimate the labor supply elasticities to the firm at the market level of men and women, each finding strong evidence of monopsonistic competition. Ransom and Oaxaca (2010) use data from a chain of grocery stores, and find labor supply elasticities of about 2.5 for men and 1.6 for women. Hirsch et al. (2010) uses administrative data from Germany to estimate elasticities ranging from 2.5-3.6 and 1.9-2.5 for men and women respectively. These studies conclude that at least one third of the wage gap between

¹⁵The 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.

men and women can be attributed to firm-level monopsony. It is important to note that this cannot be directly tested in the data used in these studies, but rather is theoretically implied by the difference in gender-specific elasticities at the market level. It should be noted that the proposed link between the gender pay gap and monopsony is not a new idea in the labor literature, with Madden (1973) devoting an entire book to this topic.

The closest analogue to this study in terms of method and data is Webber (2012), which uses linked employer employee data from the U.S. Census Bureau and an extended dynamic labor supply model to study firm-level monopsony. Webber (2012) is the first to estimate labor supply elasticities at the firm-level, and is also the first to demonstrate the link between firm-level elasticities and the earnings of workers.

4 Theoretical Model

Equilibrium search models are the theoretical basis underlying most of the recent monopsony literature. The seminal model of an economy with search frictions is that of Burdett and Mortensen (1998). They develop a model of the economy with on-the-job search 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). Also part of the Burdett-Mortensen class of search models, and of particular relevance to the present study, is Bowlus (1997). The Bowlus model allows for individuals to be out of the labor force and not be search for a job (nonparticipation) in addition to the standard employed and unemployed states. While I do not explicitly estimate either the Burdett and Mortensen or the Bowlus models in this paper, the intuition of monopsony power derived from search frictions is central to this study. The following is a description of the dynamic labor supply model which I estimate.

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 $\pi = (p-w)N(w)$ 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 $w' \geq b$ 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:

$$R(w) = R^N + \lambda \int_0^w f(x)N(x)dx \quad (19)$$

$$s(w) = \delta + \lambda(1 - F(w)) \quad (20)$$

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), and incorporates a key insight from the recent working paper by Depew and Sorensen (2011) to derive the least restrictive formula for the labor supply elasticity facing the firm currently in the literature. 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.

$$N_t(w) = N_{t-1}(w)[1 - s_{t-1}(w)] + R_{t-1}(w) \quad (21)$$

Equation (21) formalizes the definitionally true statement that a firm's employment this period is equal to the fraction of workers from last period who stay with the firm plus the number of new recruits. Noting that $N_t = \gamma N_{t-1}$ where γ is the rate of employment growth between period t-1 and t, we can rewrite Equation (21) as

$$N_t(w) = \frac{R_t(w)}{1 - (1 - s_t(w))^{\frac{1}{\gamma_t}}} \quad (22)$$

Taking the natural log of each side, multiplying by w , and differentiating we can write the elasticity of labor supply, ε , at time t as a function of the long-run elasticities of recruitment and separations, as well as the contemporary separation and growth rates.

$$\varepsilon_t = \varepsilon_R - \varepsilon_S \frac{s_t(w)}{\gamma_t + s_t(w) - 1} \quad (23)$$

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

$$\varepsilon_t = \theta^R \varepsilon_R^E + (1 - \theta^R) \varepsilon_R^N - \theta^S \varepsilon_S^E \frac{s_t^E(w)}{\gamma_t + s_t^E(w) - 1} - (1 - \theta^S) \varepsilon_S^N \frac{s_t^N(w)}{\gamma_t + s_t^N(w) - 1} \quad (24)$$

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 noemployment as functions of estimable quantities.

Looking first at the elasticity of recruitment from employment, we can write the recruitment from employment function and its derivative as

$$R^E(w) = \lambda \int_0^w f(x)N(x)dx \quad (25)$$

$$\frac{\partial R^E(w)}{\partial w} = \lambda f(w)N(w) \quad (26)$$

Combining Equations (22), (25), and (26), along with the definition of an elasticity ($\varepsilon_R^E = \frac{w}{R^E(w)} \frac{\partial R^E(w)}{\partial w}$), we get:

$$\varepsilon_R^E = \frac{w\lambda f(w)}{1 + \frac{s_t^E(w)}{\gamma_t} - \frac{1}{\gamma_t}} \quad (27)$$

In dealing with the numerator, note that the the derivative of the separation to employment function, $s^E(w) = \lambda(1 - F(w))$, is

$$\frac{\partial s^E(w)}{\partial w} = -\lambda f(w) \quad (28)$$

Combining equations (27), (28), and the definition of an elasticity ($\varepsilon_s^E = \frac{w}{s^E(w)} \frac{\partial s^E(w)}{\partial w}$), we can write the elasticity of recruitment from employment as a function of estimable quantities:

$$\varepsilon_R^E = \frac{-\varepsilon_s^E s_t^E(w)}{1 + \frac{s_t^E(w)}{\gamma_t} - \frac{1}{\gamma_t}} \quad (29)$$

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

$$\varepsilon_R^N = \varepsilon_R^E - w\theta^{R}(w)/\theta^R(w)(1 - \theta^R(w)) \quad (30)$$

This is derived from the simple definition of θ^R , the share of total recruits which come 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 (30). The second term on the right-hand side of Equation (30) 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 separation and growth rates. This study estimates the above parameters separately by gender, thus yielding gender-specific labor supply elasticities to the firm for every available firm.

The model presented above implies that, even in a world where all firms are identical and individuals possess equal ability, a difference in the job offer arrival rate across gender will lead to a gender wage gap. This is true even for firms who do not discriminate in a taste-based sense. To see how a firm's labor supply elasticity affects the wage it pays, consider a profit-maximizing firm which faces the following objective function:

$$\underset{w}{Max} \Pi = pQ(L_M) - w_M L_M(w_M) + pQ(L_F) - w_F L_F(w_F) \quad (31)$$

P is the price of the output produced according to the production function Q. The choice of wage w determines the male and female labor supplied to the firm L_M and L_F respectively. Taking first order conditions, substituting $\varepsilon = \frac{w}{L(w)} \frac{\partial L(w)}{\partial w}$, and solving for the gender-specific wage yields:

$$w_M = \frac{pQ'(L_M)}{1 + \frac{1}{\varepsilon_M}} \quad (32)$$

$$w_F = \frac{pQ'(L_F)}{1 + \frac{1}{\varepsilon_F}} \quad (33)$$

The numerator in Equation (33) is simply the marginal product of labor, and ε_M and ε_F

are the gender-specific labor supply elasticities faced by the firm. It is easy to see that in the case of perfect competition ($\varepsilon = \infty$) that the wage is equal to the marginal product of labor, but the wage is less than then marginal product for all $0 < \varepsilon < \infty$.

5 Data and Methodology

Data

This study uses linked employer-employee data from the U.S. Census Bureau to estimate the gender-specific firm level labor supply elasticities. 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).

My sample consists of quarterly observations on earnings and employment for 47 states between 1990 and 2008¹⁶. I make several sample restrictions in an attempt to obtain the most economically meaningful results. 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

¹⁶The states not in the sample are Connecticut, Massachusetts, and New Hampshire. Not all states are in the LEHD infrastructure for the entire time-frame, but once a state enters it is in the sample for all subsequent periods.

not conform with the general view of a job match between a firm and worker.

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 quarter¹⁷. I also remove all spells which span fewer than three quarters.¹⁸ This sample restriction is related to the construction of the earnings variable. 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 almost certainly underestimate 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 get an accurate measurement of 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, which corresponds approximately to the top and bottom 1 percent of observations

Additionally, I limit the analysis to firms with at least 100 total employment spells of any length over the lifespan of the firm, and 25 employment spells in each estimating equation. After making these restrictions, I am left with two samples of interest, All workers for whom I can estimate a gender-specific labor supply elasticity, and workers who work at firms where I can identify both a male and female elasticity. The first sample is made up of roughly 242 million employment spells, belonging to about 105 million unique individuals, who work at approximately 250 thousand separate firms. The sample requiring each firm to have both a male and female labor supply elasticity has roughly 183 million employment spells, belonging to about 84 million unique individuals, who work at approximately 100 thousand separate firms.

¹⁷This 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, 89.9 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.

¹⁸The relaxation of this assumption does not appreciably alter any of the reported results.

Empirical Strategy

The construction of the labor supply elasticities presented in this paper most closely represents an augmented gender-by-firm level implementation of the methodology proposed in Manning (2003), with the extension allowing for a time-varying elasticity described above.

According to the results presented in the theoretical model section, three quantities must be estimated in order to construct the labor supply elasticity measure, $(\varepsilon_S^E, \varepsilon_S^N$ and $w\theta^{R'}(w)/\theta^R(w)(1 - \theta^R(w))$), as well as the calculated recruitment share, separation share, growth rate, and separation rate for each firm. Each of the following models is run separately by gender for every firm in the sample, where the unit of observation is an employment spell. Looking first at the separation elasticities, I model separations to nonemployment as a Cox proportional hazard model given by

$$\lambda^N(t|\beta^{N,sep}\log(earnings)_i + X_i\gamma^{N,sep}) = \lambda_0(t) \exp(\beta^{N,sep}\log(earnings)_i + X_i\gamma^{N,sep}) \quad (34)$$

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, and X is a vector of explanatory variables including race, age, education, firm size, and year control variables (time-invariant firm characteristics such as industry cannot be included because the model is run at the firm level). While the entire sample will be 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 represents an estimate of the separation elasticity to nonemployment. In an analogous setting, I model separations to employment as

$$\lambda^E(t|\beta^{E,sep}\log(earnings)_i + X_i\gamma^{E,sep}) = \lambda_0(t) \exp(\beta^{E,sep}\log(earnings)_i + X_i\gamma^{E,sep}) \quad (35)$$

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 represents an estimate of the separation elasticity to employment. To estimate the third quantity needed for equation (24), $w\theta^R(w)/\theta^R(w)(1 - \theta^R(w))$, Manning (2003) shows that this is equivalent to the coefficient on log earnings when estimating the following logistic regression

$$P_{rec} = \frac{\exp(\beta^{E,rec} \log(\text{earnings})_i + X_i \gamma^{E,rec})}{1 + \exp(\beta^{E,rec} \log(\text{earnings})_i + X_i \gamma^{E,rec})} \quad (36)$$

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 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 (24) to produce an estimate of the labor supply elasticity facing each firm.¹⁹

To provide some intuition on the models being estimated, consider the analysis of separations to employment. A large (in absolute value) coefficient on the log earnings variable 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 small coefficient implies that the employer can lower the wage rate without seeing a substantial decline in employment. One concern with this procedure is that this measure of monopsony power is actually proxying for high-wage firms, reflecting an efficiency wage view of the economy where firms pay a wage considerably above the market wage in exchange for lower turnover. This is directly testable, and is rejected as an explanation later in the paper.

¹⁹Each 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.

Analysis

In order to directly estimate the impact of firm-level monopsony on the gender pay gap, we must estimate two quantities: the male-female gap in labor supply elasticities and the impact of the labor supply elasticity on earnings. The elasticity gap can be derived from the above results. The impact of the labor supply elasticity on earnings can be estimated from the following equation.

$$\log(\text{quarterly earnings}_{ij}) = \beta \text{elasticity}_{jg} + \gamma X_{ij} + \delta Y_j + \theta Z_i + \varepsilon_{ij} \quad (37)$$

The dependent variable is the natural log of individual i 's quarterly earnings in employment spell j . The elasticity variable represents the gender specific elasticity of firm j and gender g . 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, education²⁰, race, ethnicity, year 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.

6 Results

Summary Statistics

Table 2.1 reports summary statistics for both men and women in my sample. Since the unit of observation is the employment spell, and only dominant jobs are included, some statistics deviate slightly from typical observational studies of the labor market. The average

²⁰Reported educational attainment is only available for about 10 percent of the sample, although sophisticated imputations of education are available for the entire sample. The results presented in this paper correspond to 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.

employment spell lasts about two and a half years, with more than sixty percent of spells resulting from a move from another job. Of particular importance to this study, is that the raw earnings gap between men and women is about 0.34 log points. The quarterly nature of the LEHD data make it difficult to precisely identify²¹ 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).

Variable	Men		Women	
	Mean	Std Dev	Mean	Std Dev
Age	38	14	38	14
Tenure (Quarters)	10.2	11.1	10.1	10.83
Log(Quarterly Earnings)	8.68	1	8.34	0.94
White	0.78	0.42	0.76	0.43
Hispanic	0.15	0.36	0.13	0.33
< High School	0.17	0.37	0.13	0.33
High School Degree	0.29	0.46	0.28	0.45
Some College	0.3	0.46	0.34	0.47
College Degree+	0.24	0.43	0.25	0.43

To give the reader some intuition about the type of firms in my sample, the median firm employs roughly 400 workers, hiring 75, in a given quarter. keep in mind that these statistics are not point in time calculations, but rather totals throughout an entire quarter. Additionally, remember that these are at the firm (state-level) rather than at the establishment (individual unit) level.

Firm-Level Measure

Table 2.2 presents the elasticities estimated through Equations (34)-(36) broken down by gender. The first four columns report the average (weighted by employment) firm-level elas-

²¹The definition used in this paper requires an individual to have no reported earnings for an entire quarter following an employment spell to be defined as a separation to nonemployment, with all other separations coded as a separation to employment. This definition was chosen because it lead to the most conservative (least monopsonistic) results, although the differences were small. The other methods tried involved imputing the time during the quarter at which employment stopped/started based on a comparison of the earnings reported in the last/first quarter to a quarter in which I know the individual worked the entire quarter.

ticities 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.

Table 2.2: Firm-Level Labor Supply Elasticities					
Model	ε_R^E	ε_R^N	ε_S^E	ε_S^N	ε
Male Elasticities					
No Controls	.47	.11	-.47	-.62	.96
Full Model	.54	.13	-.54	-.7	1.09
Female Elasticities					
No Controls	.39	.09	-.39	-.62	.83
Full Model	.45	.1	-.45	-.7	.94

The first row of each panel represents estimates from equations (34)-(36) where the only regressor in each model is log earnings. The second row estimates the same equations, and includes age, age-squared, firm size, along with indicator variables for nonwhite, Hispanic, completing a high school diploma, some college, and college degree or greater, and year effects. 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 facing the firm.

The results detailed in Table 2.2 are notable in two regards. First, the average labor supply elasticities (0.94 for women and 1.09 for men) are fairly monopsonistic, implying a high degree of market power for firms²². This is consistent with previous work utilizing dynamic labor supply models such as Manning (2003) or Webber (2012). It is important to note that Webber (2012) finds that firms do not appear to exploit all of their wage-setting power. Second, the difference between the male and female labor supply elasticities is considerable (1.09 to 0.94)²³, with the gap implying men should earn approximately 7.5% more than women solely as a result of the disparity in labor supply elasticities²⁴. This corresponds to about 22% of the raw gender wage gap in my sample, and 33% of the gap when basic

²²A number of robustness check (equivalent to Webber (2012)) were run to test for threats to identification such as endogenous mobility. No significant differences in the estimated labor supply elasticities were found under any of these alternative specifications. Results are available upon request.

²³Interestingly, this gap has remained nearly constant throughout the timeframe of my sample.

²⁴Calculated using Equations (33) and (33)

observables are controlled for (based on the regressions to be presented below). Finally, we see that the difference in labor supply elasticities between men and women is driven by the difference between the separation and recruitment elasticities to/from employment. In the context of a search model, this implies that the increased search frictions for women are due more to a lower job offer arrival rate as opposed to a higher job destruction rate.

Table 2.3 displays information about the distribution of labor supply elasticities for men and women in two different samples. The first sample, the same used in Table 2.2, represents all men and women for whom I was able to estimate a labor supply elasticity (given the restrictions mentioned in the data section). The second sample only includes individuals who work at firms where I am able to estimate both a male and female labor supply elasticity. As shown in Table 2.3, there is only a small gender differential when looking within firms. Thus nearly the entire elasticity gap between men and women is driven by differences across firms, with women disproportionately working at low-elasticity (and therefore low-wage) firms. This conforms with predictions from the early gender differential literature (Blau, 1977; Groshen, 1991) and the equilibrium search model of Bowlus (1997).

Table 2.3: Distribution of Estimated Firm-Level Labor Supply Elasticities						
		Percentiles				
	Mean	10th	25th	50th	75th	90th
All workers						
Men	1.09	0.22	0.45	0.78	1.24	1.94
Women	0.94	0.23	0.43	0.72	1.08	1.58
Only firms with both elasticities						
Men	0.98	0.23	0.44	0.75	1.15	1.69
Women	0.94	0.26	0.46	0.74	1.08	1.54

*Three separate regressions, corresponding to equations (34)-(36), were estimated separately by gender 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 (24) 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 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 2.4 reports average labor supply elasticities broken down by NAICS sector. The most competitive industries among men are the manufacturing and mining/oil/natural gas sectors, while the least competitive are the administrative support and accomodation/food service sectors. Among women, the most competitive industries are manufacturing and transportation, while the least competitive are the administrative support and health care sectors. The low elasticity for female healthcare workers is consistent with the focus of most of the early monopsony literature's focus on the market for nurses. The male labor supply elasticity is greater than or equal to the female labor supply elasticity in 18 of the 20 sectors, and only slightly smaller in the other two. By far, the greatest elasticity differential can be found in the construction industry, where men face an elasticity of 1.39 compared to 0.92 for women.

Table 2.4: Mean Labor Supply Elasticity by NAICS Sector and Gender		
NAICS Sector	Male Labor Supply Elasticity	Female Labor Supply Elasticity
Agriculture	1.35	1.25
Mining/Oil/Natural Gas	1.51	1.3
Utilities	1.18	1.03
Construction	1.39	0.92
Manufacturing	1.67	1.66
Wholesale Trade	1.38	1.27
Resale Trade	1.01	0.96
Transportation	1.44	1.38
Information	1.11	1.11
Finance and Insurance	1.13	1.2
Real Estate and Rental	0.99	0.94
Professional/Scientific/Technical Services	1.06	1.03
Management of Companies	1.08	1.04
Administrative Support	0.64	0.64
Educational Services	0.95	0.9
Health Care and Social Assistance	0.77	0.75
Arts and Entertainment	0.96	0.87
Accommodation and Food Services	0.76	0.84
Other Services	1.04	0.93
Public Administration	1.28	1.11

*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 (34)-(36), were estimated separately by gender 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 (24) 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 ethnicity, racial status, and education level. Employer controls include the number of employees working at the firm. Year effects are included in all models.

Now that we have estimated the gender elasticity gap, we now turn to the question of how much of the gender earnings gap can be explained by the difference in labor supply elasticities. Previous studies, which only were able to estimate elasticities at the market level, were forced to interpolate the impact on the gender pay gap. As mentioned above, the theoretical impact implied by my results is men earning 7.5% more than women due to

differences in search frictions. Table 2.5 presents a series of log-earnings regressions²⁵ which allow me to directly estimate this impact due to the firm-level nature of the elasticities generated by this study. In the model with the most detailed set of controls (firm fixed-effects) I find a coefficient of 0.12 on the gender-specific labor supply elasticity, which implies that a labor supply elasticity differential of 0.15 will lead to a gender earnings gap of 2.0%, less than half of the theoretically predicted value²⁶. This corresponds to about 6% of the raw gender wage gap in my sample and 9% of the gender wage gap after controlling for the observables available in this study.

Also of note in Table 2.5 is how the coefficient on the gender-specific labor supply elasticity variable changes as person and firm fixed effects are added. The noticeable increase in the coefficient, both when firm and person effects are added to the model, imply that on average low-wage firms have higher labor supply elasticities, and low-wage workers have higher labor supply elasticities. This is in line with the current thinking regarding monopsony power and its interaction with skilled and unskilled labor (Stevens, 1994; Muehleman et al., 2010).

²⁵Table 2.5 depicts regressions run on the sample of workers who work at firms where both a male and female labor supply elasticity can be estimated. These regressions were also run on the entire sample, as well as on only the male and female samples, with nearly identical results.

²⁶ $(\exp(.2) - 1) * .15$

Table 2.5: Impact of Search Frictions on Earnings

	0.14	0.12	0.08	0.05	0.05	0.06	0.12
Coefficient on labor supply elasticity							
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	No
Firm fixed-effects	No	No	No	No	No	No	Yes
R-Squared	0.005	0.233	0.308	0.329	0.336	0.815	0.90

*A pooled national sample of all dominant employment spells, at firms which have estimated elasticities for each gender, 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 are greater than 200 in all models. Clustering these standard errors at various levels does not affect the statistical significance. All standard errors and other estimated coefficients are available upon request. There are approximately 183,000,000 observations in each specification.

There is reason to believe that the estimates in Table 2.5 are lower bounds of the true impact of firm monopsony power on earnings. Each labor supply elasticity is a weighted average of many more precisely defined elasticities which would more accurately measure a firm's market power over a particular individual. For example, firms likely face different supply elasticities for every occupation, and potentially different elasticities across race and gender groups. From a measurement error perspective, regressing the log of earnings on the average labor supply elasticity to the firm would attenuate the estimates relative to the ideal scenario where I could separately identify every occupation specific elasticity. Nevertheless, the measurement error present is unlikely to be of the magnitude necessary to attenuate the estimate by more than half.

While these results are clear evidence that firm-level monopsony contributes to the gender

pay gap, as has been documented on a less detailed scale by several other studies, these results provide two key insights into the impact of imperfect competition on the gender pay gap. First, on average, the gap between the male and female labor supply elasticities is quite small within firms which employ a nontrivial number of both men and women. Instead, the gap is primarily driven by disproportionate numbers of men (women) working at high (low) elasticity firms. A second important contribution of this study is that firms do not utilize all of the wage setting power available to them when it comes to the gender pay gap. The results suggest that women would earn about 7.5 percent less than men, holding all else constant, as a result of increased search frictions. However, I find that these search frictions only cost women about 3.3 percent of their earnings relative to their male counterparts (the analogous statistics for firms which employ nontrivial workers of each gender are 2.0 and 0.9 percent respectively). Given the existence of pay equity laws and substantial social pressure promoting gender equality, this result is not surprising. A similar point was first made by Bronfenbrenner (1956), which argued that firms likely possess substantial wage-setting power but are unlikely to exercise all or most of it.

7 Conclusion

The gender pay gap is one of the most studied topics in modern labor economics. Despite this intense focus, only recently have studies considered the impact that imperfect competition in the labor market may have on the gender pay differential. Furthermore, due to data constraints, the recent empirical studies which find evidence of different degrees of search frictions between men and women are unable to directly estimate the impact of these frictions on the gender pay gap.

This study uses linked employer-employee data to estimate the labor supply elasticity facing the firm, separately by gender, for a comprehensive sample of U.S. firms. Using a dynamic model of labor supply, which identifies the labor supply elasticity to the firm off

of job to job transitions, I find evidence of substantial search frictions in the economy, with females facing a higher level of frictions than males. However, the majority of the gender gap in labor supply elasticities is driven by across firm sorting rather than within firm differences, a feature predicted by the Bowlus (1997) equilibrium search model, but which has not been previously documented.

On average, I find that males face a labor supply elasticity 0.15 points higher than females, a differential which leads to 2.0% lower earnings for women (or about 9% of the adjusted gender earnings gap). However, this is slightly less than half of the theoretically implied impact which the previous literature has been forced to rely upon.

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Part III

Labor Mobility and the Great Recession

Abstract

Using linked employer-employee data from the United States Census Bureau, I calculate the impact of the Great Recession on labor market frictions. To generate these measures, I use a dynamic model similar to that of Manning (2003) and estimate the labor supply elasticity from job-to-job flows. I estimate that the labor supply elasticity to the firm declined by approximately 0.19 points (1.20 to 1.01) following the financial crisis of 2008. Furthermore, this decline cost workers about 2.4 percent in 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 higher during poor economic climates. This conforms with the predictions of recent macroeconomic search models which imply that frictions in the economy may actually reduce employment fluctuations.

1 Introduction

The severe labor market downturn caused by the Great Recession is 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). Furthermore, recent work by Lazear and Spletzer (2012) highlights the lack of labor market churning during this time period. 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 their reservation wages (i.e. unemployment insurance) rather than with the wages of other firms.

Recent research (Manning, 2003; Hirsch et al., 2010; Ransom and Oaxaca, 2010; Webber, 2012) has highlighted both the prevalence and importance of frictions in the labor market which lead to less than perfect mobility for workers. While this new literature, up to this point, 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 firms between 1998 and 2011. The only previous paper to look at time series variation of the labor supply elasticity, Depew and Sorensen (2011), did so for a single firm in the early to mid 1900's. 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 about 16% from its peak (1.20) to a low of 1.01 in late 2010. Based on a series of earnings regressions, this decline led to earnings losses of approximately 2.4 percent. I also find substantial differences in the decline of labor market competitiveness across industries.

I estimate that in a good economy, on average firms in monopsonistic 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 among monopsonistic firms. Furthermore, I find that during the Great Recession relatively monopsonistic firms had a higher growth rate than relatively competitive firms. The 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 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). In her seminal work, Robinson formulated the analysis which is still taught in undergraduate labor economics courses. Monopsony literally means “one buyer”, and 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.

It should be pointed out that in the “new monopsony” framework, the word monopsony is

synonymous with the following phrases: monopsonistic competition, imperfect competition, finite labor supply elasticity, or upward sloping labor supply curve to the firm. While the classic monopsony model is based on the idea of a single firm as the only outlet for which workers can supply labor, the new framework defines monopsony as any departure from the assumptions of perfect competition. Additionally, the degree of monopsonistic competition may vary significantly across labor markets, and even across firms within a given labor market.

Many studies have provided suggestive evidence of an imperfectly 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). For instance, Goux and Maurin (1999) conclude that on average firm effects alter an individual's wage by more than 20 percent. Furthermore, they find these firm effects are related more to firm characteristics such as size rather than productivity, implying that the firm effects are not simply absorbing workers' unmeasured marginal product of labor.

A relatively new branch of labor economics which focuses on the initial labor market conditions when a worker enters the labor market may also provide insight into the mobility of workers. A number of studies (Oyer, 2006, 2008; Genda and Kondo, 2010; Kahn, 2010) find persistent and negative wage effects from entering the labor market in a bad economy, lasting for at least 20 years. Additionally, 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. The persistent effects found in all of these studies provide further suggestive evidence of significant long-run frictions in the labor market.

Most of the theoretical work done on this topic resides in the search theory literature, with major contributions coming from Burdett and Mortensen (1998) and Shimer (2005) to name a few²⁷. This line of research has given rise to a "new monopsony" literature, pop-

²⁷See Mortensen (2003) or Rogerson et al. (2005) for a review of this literature

ularized by Alan Manning's (Manning, 2003) careful analysis of labor-related topics absent the assumption of perfect competition. 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.

Even if the existence of monopsony power is accepted, estimating the degree of market power possessed by a firm is not a simple task. Economists since Bunting (1962) have searched for empirical evidence of monopsony, with the predominant method being the use of 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; Feldman and Scheffler, 1982; Hirsch and Schumacher, 1995; Link and Landon, 1975; Adamache and Sloan, 1982; Link and Settle, 1979). This market lends itself to monopsony because nurses have a highly specific form of human capital and there are many rural labor markets where hospitals are the dominant employer. Despite the relatively large literature on this narrow labor market, 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 elasticity²⁸. 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. In a novel approach using German administrative data, Schmieder (2010) finds evidence of a positive

²⁸The 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.

sloping labor supply curve through an analysis of new establishments.

Using a dynamic approach similar to this study, Ransom and Oaxaca (2010) and Hirsch et al. (2010) both separately estimate the labor supply elasticities to the firm of men and women, each finding strong evidence of monopsonistic competition. Ransom and Oaxaca (2010) use data from a chain of grocery stores, and find labor supply elasticities of about 2.5 for men and 1.6 for women. Hirsch et al. (2010) uses administrative data from Germany to estimate elasticities ranging from 2.5-3.6 and 1.9-2.5 for men and women respectively. Applying this approach to survey data, Manning (2003) finds labor supply elasticities ranging from 0.68 in the NLSY to 1.38 in the PSID. In a developing country context, Brummund (2011) uses a novel structural production function approach, and finds strong evidence of monopsony in Indonesian labor markets, estimating labor supply elasticities between 0.6 and 1.0.

Depew and Sorensen (2011) derive a time-varying measure of the labor supply elasticity to the firm, and analyze the cyclical nature of Ford's labor supply elasticity in the early to mid 1900's. Webber (2012), the closest analogue to this study, uses linked employer employee data from the U.S. Census Bureau and an extended dynamic labor supply model to study firm-level monopsony. Webber (2012) is the first to estimate a comprehensive set of labor supply elasticities at the firm-level, calculating an average worker-weighted elasticity of 1.08, and is also the first to demonstrate the link between firm-level elasticities and the earnings of workers.

Little theoretical work has been done regarding the impact of labor market frictions over the business cycle, however, a recent search model presented in Rogerson and Shimer (2011) is of particular relevance to this study. Their model suggests 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 costly labor adjustment costs.

3 Theoretical Model

A central feature of perfect competition is the law of one wage, that all workers of equal ability should be paid the same market clearing wage. In an attempt to explain how wage dispersion can indeed be an equilibrium outcome, Burdett and Mortensen (1998) 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 $\pi = (p-w)N(w)$ 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 $w' \geq b$ 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:

$$R(w) = R^N + \lambda \int_0^w f(x)N(x)dx \quad (38)$$

$$s(w) = \delta + \lambda(1 - F(w)) \quad (39)$$

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), and incorporates a key insight from the recent working paper by Depew and Sorensen (2011) to derive the least restrictive formula for the labor supply elasticity facing the firm currently in the literature. 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.

$$N_t(w) = N_{t-1}(w)[1 - s_{t-1}(w)] + R_{t-1}(w) \quad (40)$$

Equation (40) formalizes the definitionally true statement that a firm's employment this period is equal to the fraction of workers from last period who stay with the firm plus the number of new recruits. Noting that $N_t = \gamma N_{t-1}$ where γ is the rate of employment growth between period $t-1$ and t , we can rewrite Equation (40) as

$$N_t(w) = \frac{R_t(w)}{1 - (1 - s_t(w))^{\frac{1}{\gamma_t}}} \quad (41)$$

Taking the natural log of each side, multiplying by w , and differentiating we can write the elasticity of labor supply, ε , at time t as a function of the long-run elasticities of recruitment and separations, as well as the contemporary separation and growth rates.

$$\varepsilon_t = \varepsilon_R - \varepsilon_S \frac{s_t(w)}{\gamma_t + s_t(w) - 1} \quad (42)$$

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

$$\varepsilon_t = \theta^R \varepsilon_R^E + (1 - \theta^R) \varepsilon_R^N - \theta^S \varepsilon_S^E \frac{s_t^E(w)}{\gamma_t + s_t^E(w) - 1} - (1 - \theta^S) \varepsilon_S^N \frac{s_t^N(w)}{\gamma_t + s_t^N(w) - 1} \quad (43)$$

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 noemployment as functions of estimable quantities.

Looking first at the elasticity of recruitment from employment, we can write the recruitment from employment function and its derivative as

$$R^E(w) = \lambda \int_0^w f(x) N(x) dx \quad (44)$$

$$\frac{\partial R^E(w)}{\partial w} = \lambda f(w) N(w) \quad (45)$$

Combining Equations (41), (44), and (45), along with the definition of an elasticity ($\varepsilon_R^E = \frac{w}{R^E(w)} \frac{\partial R^E(w)}{\partial w}$), we get:

$$\varepsilon_R^E = \frac{w \lambda f(w)}{1 + \frac{s_t^E(w)}{\gamma_t} - \frac{1}{\gamma_t}} \quad (46)$$

In dealing with the numerator, note that the the derivative of the separation to employ-

ment function, $s^E(w) = \lambda(1 - F(w))$, is

$$\frac{\partial s^E(w)}{\partial w} = -\lambda f(w) \quad (47)$$

Combining equations (46), (47), and the definition of an elasticity ($\varepsilon_s^E = \frac{w}{s^E(w)} \frac{\partial s^E(w)}{\partial w}$), we can write the elasticity of recruitment from employment as a function of estimable quantities:

$$\varepsilon_R^E = \frac{-\varepsilon_S^E s_t^E(w)}{1 + \frac{s_t^E(w)}{\gamma_t} - \frac{1}{\gamma_t}} \quad (48)$$

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

$$\varepsilon_R^N = \varepsilon_R^E - w\theta^R(w)/\theta^R(w)(1 - \theta^R(w)) \quad (49)$$

This is derived from the simple definition of θ^R , the share of total recruits which come 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 (49). The second term on the right-hand side of Equation (49) 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 separation and growth rates.

4 Data and Methodology

Data

The Longitudinal Employer Household whichDynamics (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 will use in this study. First, I use a set of employment spells coming from many different firms to obtain estimates of the labor supply elasticity for each firm. This sample is constructed in a similar way to Webber (2012) (although the sample is slightly different because this study uses fewer states, but more years of data). The second sample, also the 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 and 2011²⁹. I make several sample restrictions in an attempt to obtain the most economically meaningful results. 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.

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

²⁹The 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. These were chosen to have a consistent panel of states for all years of my sample (16 other states do not enter the LEHD infrastructure until after 1998).

a given quarter³⁰. I also remove all spells which span fewer than three quarters.³¹ This sample restriction is related to the construction of the earnings variable. 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 almost certainly underestimate 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 get an accurate measurement of 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, which corresponds approximately to the top and bottom 1 percent of observations. Additionally, only firms which have greater than 25 separations to employment, 25 separations to unemployment, and 25 recruits from employment over the lifespan of the firm are considered, this is done to ensure there is sufficient data to estimate the relevant elasticities. This reduces the analysis sample to 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 an augmented 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.

³⁰This 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, 89.9 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.

³¹The relaxation of this assumption does not appreciably alter any of the reported results.

Dynamic Measure

The simplest way to estimate the labor supply elasticity to the firm would be to regress the natural log of firm size on the natural log of firm wages. However, even when controlling for various demographic characteristics, this is deemed to produce a potentially biased estimate³². 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 (43) to produce an estimate of the labor supply elasticity to the firm.

To my knowledge, only Hirsch et al. (2010) has used a similar, but considerably more restrictive, method with administrative data which yielded an economy-wide estimate of the average labor supply curve facing the firm. Manning (2003) also estimates an economy-wide measure of the degree of monopsony using surveys such as the National Longitudinal Survey of Youth (NLSY) 1979. One of the major contributions of this paper is that I estimate the labor supply elasticities for each firm, rather than the average over the whole economy. Additionally, these prior studies imposed a steady-state assumption on their model, which the model in this paper does not impose. Estimating the labor supply elasticities at the firm level does have several advantages. First, the estimation of each of the elasticity components is much more flexible than even the least constrained specifications of Hirsch et al. (2010). Second, I am able to use the measures as an explanatory variable, and can test a number of different models. Finally, I am able to examine the effect of market power on earnings at each point in the market power distribution, rather than examining only the average effect. This is particularly important because theory predicts significant nonlinear effects relating to the labor supply elasticity and a firm's ability to mark down wages (Pigou, 1924). However, this strategy has the drawback that I am unable to estimate the relevant parameters, and thus the labor supply elasticity, for the smallest firms (sample restrictions are discussed in the data section).

³²The 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

According to the results presented in the theoretical model section, three quantities must be estimated in order to construct the labor supply elasticity measure, $(\varepsilon_S^E, \varepsilon_S^N$ and $w\theta^{R'}(w)/\theta^R(w)(1 - \theta^R(w))$), as well as the calculated separation and growth rates for each firm. Each of the following models will be 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

$$\lambda^N(t|\beta^{N,sep}\log(earnings)_i + X_i\gamma^{N,sep}) = \lambda_0(t) \exp(\beta^{N,sep}\log(earnings)_i + X_i\gamma^{N,sep}) \quad (50)$$

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,³³ 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 represents an estimate of the separation elasticity to nonemployment. In an analogous setting, I model separations to employment as

$$\lambda^E(t|\beta^{E,sep}\log(earnings)_i + X_i\gamma^{E,sep}) = \lambda_0(t) \exp(\beta^{E,sep}\log(earnings)_i + X_i\gamma^{E,sep}) \quad (51)$$

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 represents an estimate of the separation elasticity to employment. To estimate the third quantity needed for equation (43),

³³As 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.

$w\theta^{R(w)}/\theta^R(w)(1 - \theta^R(w))$, Manning (2003) shows that this is equivalent to the coefficient on log earnings when estimating the following logistic regression

$$P_{rec} = \frac{\exp(\beta^{E,rec}\log(earnings)_i + X_i\gamma^{E,rec})}{1 + \exp(\beta^{E,rec}\log(earnings)_i + X_i\gamma^{E,rec})} \quad (52)$$

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 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 (43) to produce an estimate of the labor supply elasticity facing each firm.³⁴

To provide some intuition on the models being estimated, consider the analysis of separations to employment. A large (in absolute value) coefficient on the log earnings variable 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 concern with this procedure is that this measure of monopsony power is actually proxying for high-wage firms, reflecting an efficiency wage view of the economy where firms pay a wage considerably above the market wage in exchange for lower turnover. This is much more of a 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. The logic behind this difference is that in the full economy model cross-sectional variation in the level of earnings is used to identify the labor supply

³⁴Each 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.

elasticity. In a firm-specific model, however, the labor supply elasticity of firm A does not mechanically depend on the level of earnings at firm B. This efficiency wage hypothesis will be directly tested.

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 :

$$\log(\text{quarterly earnings}_{ij}) = \beta \text{elasticity}_j + \gamma X_{ij} + \delta Y_j + \theta Z_i + \varepsilon_{ij} \quad (53)$$

The dependent variable is the natural log of individual i 's quarterly earnings in employment spell 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, education³⁵, gender, race, ethnicity, year 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 then 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:

³⁵Reported educational attainment is only available for about 15 percent of the sample, although sophisticated imputations of education are available for the entire sample. The results presented in this paper correspond to 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.

$$Rate_{jt} = \beta elasticity_j + \gamma Quarter_t + \delta Elasticity * Quarter_{jt} + \theta X_{jt} + \varepsilon_{jt} \quad (54)$$

The dependent variable represents the growth, separation, or hiring rate of firm j in quarter t . Elasticity is firm j 's long run labor supply elasticity (the time-varying elasticity is not used because the separation and growth rates are explicitly part of the time-varying model). 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 3.1 reports both employment spell and firm-level summary statistics. Since the unit of observation is the employment spell rather than the individual, and only dominant jobs are included, some statistics deviate slightly from typical observational studies of the labor market (such as a nearly even split of job spells between men and women). 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 identify³⁶ 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).

³⁶The definition used in this paper requires an individual to have no reported earnings for an entire quarter following an employment spell to be defined as a separation to nonemployment, with all other separations coded as a separation to employment. This definition was chosen because it lead to the most conservative (least monopsonistic) results, although the differences were small. The other methods tried involved imputing the time during the quarter at which employment stopped/started based on a comparison of the earnings reported in the last/first quarter to a quarter in which I know the individual worked the entire quarter.

Table 3.1: 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	

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 is that statistics are not point in time estimates, but rather totals throughout an entire quarter. Finally, remember that these are at the firm (state-level) rather than at the establishment (individual unit) level.

Monopsony over the Business Cycle

Table 3.2 and Table 3.3 present information about the elasticities estimated through Equations (50)-(52). Since the results in these tables are quite similar to those of Webber (2012) I will not spend much time describing them. The first four columns of Table 3.2 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. As shown in Table 3.3, I estimate a mean (worker-weighted) labor supply elasticity of 1.17.

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

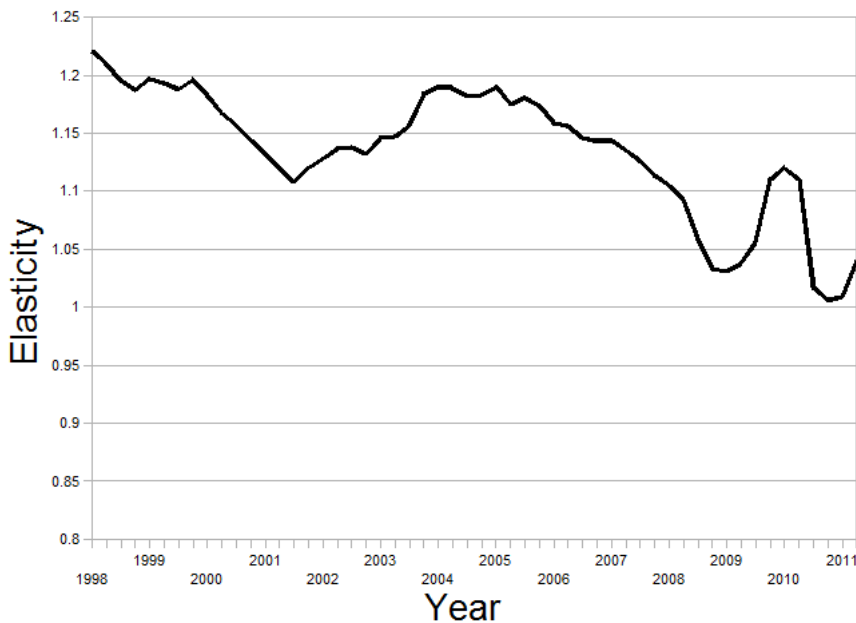
The first row represents estimates from equations (50)-(52) where the only regressor in each model is log earnings. The second row estimates the same equations, and includes age, age-squared, along with indicator variables for female, nonwhite, Hispanic, education category controls, and year effects. 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 3.3: Distribution of Estimated Firm-Level Labor Supply Elasticities					
Percentiles					
Mean	10th	525th	50th	75th	90th
1.17	0.26	0.5	0.85	1.35	2.13

*Three separate regressions, corresponding to equations (50)-(52), 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 (43) 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.

Figure 3.1 plots the labor supply elasticity between 1998 and 2011 for the 31 states enumerated in the Data section. For 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 peak of 1.20 occurring in 2005 quarter 1.01. 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.

Figure 3.1: The Labor Supply Elasticity to the Firm Over Time



But what does this mean in terms of worker welfare? Theoretically, a decline in the

labor supply elasticity from 1.19 to 1 leads to earnings losses of 8.7 percent³⁷. To test the impact empirical impact of this decline, Table 3.4 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 1.19 to 1.00 led to earnings losses of 2.4 percentage points.

³⁷Based on the profit-maximizing condition $w = \frac{pQ'(L)}{1+\frac{1}{\epsilon}}$ where w represent the wage, the numerator is the marginal product of labor, and ϵ is the elasticity.

	0.14	0.12	0.08	0.05	0.05	0.06	0.12
Coefficient on labor supply elasticity	0.14	0.12	0.08	0.05	0.05	0.06	0.12
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	No
Firm fixed-effects	No	No	No	No	No	No	Yes
R-Squared	0.005	0.238	0.312	0.331	0.338	0.784	0.90

*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 3.5 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, accomodation/food services saw relatively mild declines in competition (4 percent). Skill-biased technological change may be able to partially explain the relative declines for these industries.

Table 3.5: 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 (50)-(52), 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 (43) 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 3.6 displays results from estimating Equation (54) 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 controls.

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.

Table 3.6: Employment Behavior and the Labor Supply Elasticity

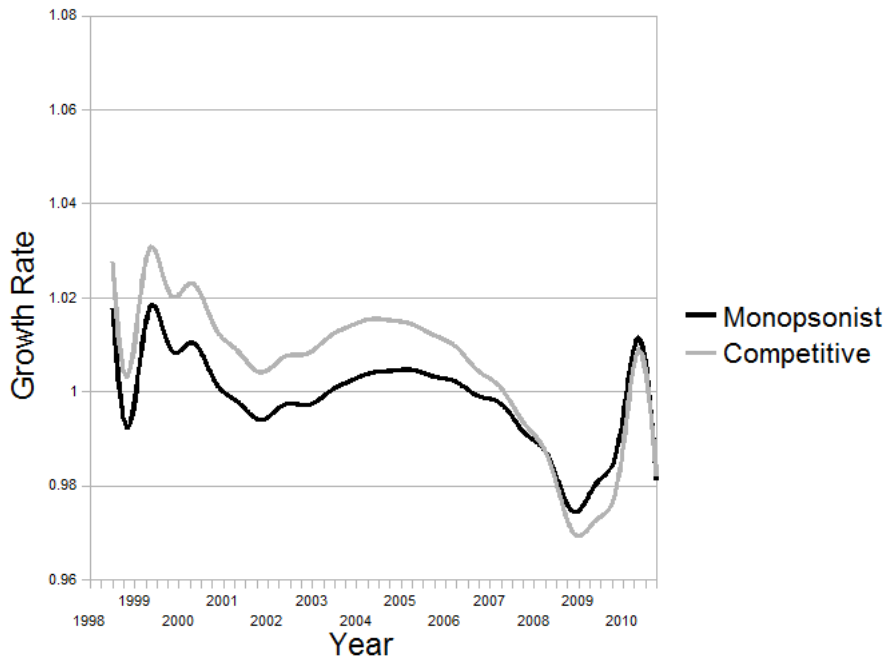
	Growth Rate		Hiring Rate		Separation Rate	
	No	Controls	No	Controls	No	Controls
	Controls		Controls		Controls	
Coefficient	.004	.005	-.022	-.013	-.025	-.016

The results represent the coefficient on labor supply elasticity when estimating Equation (54) at the firm level both 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.

Figure 3.2 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 (54) 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, which persists to the end of the current data series.

Figure 3.2: Competitive and Monopsonistic Quarterly Growth Rates



Figures 3.3 and 3.4 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.

Figure 3.3: Competitive and Monopsonistic Quarterly Hiring Rates

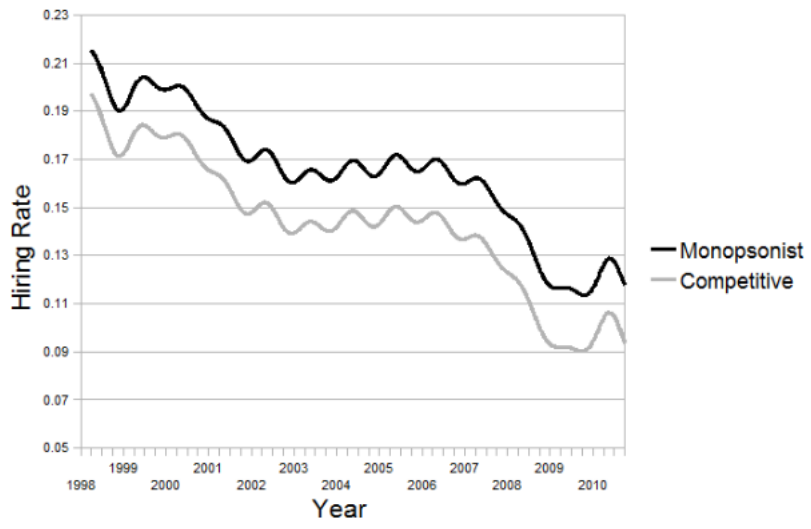
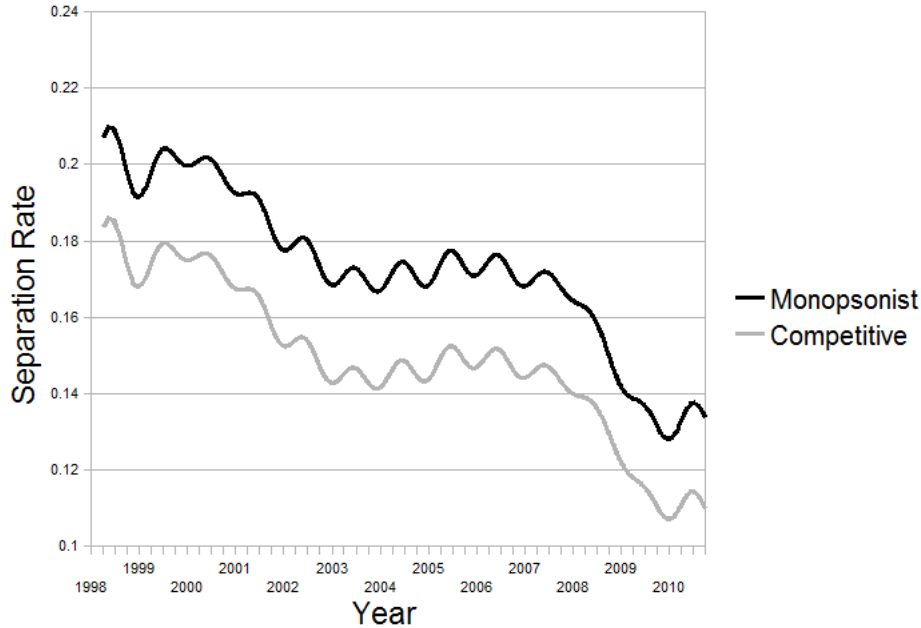


Figure 3.4: Competitive and Monopsonistic Quarterly Separation Rates



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 are an important determinant of 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 are 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 financial crisis of 2008 led to a substantial increase in the search frictions which lead to an imperfectly competitive labor market. Using data from the Longitudinal Employer Household Dynamics (LEHD) infrastructure, I use a dynamic model approach similar to that of Manning (2003) to identify firm level labor supply elasticities off of job-to-job transitions. I find that the average (worker-weighted) labor supply elasticity facing the firm dropped from a peak of 1.19 in 2005 to a low point of 1.00 in the fourth quarter of 2010. Based on a series of earnings regressions, this decline led to earnings losses of approximately 2.4 percent. I also find heterogeneity across industries in the decline of the labor supply elasticity, with scientific/technical services being the most affected industry.

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.

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