

# Variation in Monopsonistic Behavior Across Establishments: Evidence From the Indonesian Labor Market

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**Abstract** Firms are able to behave monopsonistically when hiring workers because of frictions in the labor market. These frictions have traditionally been thought of as moving costs that separate labor markets. More recent theoretical work has shown that individual firms can have market power independent of the labor market due to other frictions, such as search frictions or information asymmetries. However, current techniques for measuring market power are unable to separate the firm determinants of market power from the market determinants. This paper proposes a new method for measuring monopsonistic behavior that yields a firm-specific measurement. I apply this measure to the Indonesian manufacturing sector, where I argue labor market frictions are more prevalent than in developed countries. To my knowledge, this is the first empirical evidence for monopsonistic behavior of establishments in an emerging economy. I find that over half of the manufacturing establishments have a significant amount of market power, with the median firm facing a labor supply elasticity of 0.52. I then show that individual establishment characteristics explain more of the variation in monopsonistic behavior than the characteristics of the labor market in which the establishment participates in.

**Keywords:** Monopsony; Labor Markets; Indonesia.

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# 1 Introduction

How much market power do individual firms<sup>1</sup> have in their labor market, and is that power more attributable to specific firm characteristics or the labor market the firm participates in? Monopsony has traditionally been considered a market characteristic where individual firms face the upward-sloping labor supply curve of the market (Robinson 1933). However, recent theoretical work has shown that individual firms can have market power above and beyond the level of monopsony determined by the market (Burdett and Mortensen 1998, Manning 2003). Yet, standard empirical techniques for measuring monopsony operate at an aggregate level, preventing analysis of the market power of individual firms. I propose a new method for measuring market power at the firm-year level, which enables me to investigate the relative importance of firm and market-level characteristics in determining market power.

This paper makes three contributions to the literature. First, I extend and combine existing empirical techniques to develop a new method for measuring market power that yields firm-year specific measurements. Second, I apply this method to Indonesia, providing to my knowledge, the first evidence for monopsonistic behavior of firms in an emerging economy. Lastly, I use the distribution of market power across firms to show that individual firm characteristics are more important in explaining a firm's market power than is the labor market the firm participates in.

A standard empirical measure of monopsony<sup>2</sup> is the difference between a worker's marginal revenue product and the wage he or she is paid, normalized by the wage (Pigou 1924)<sup>3</sup>. The inverse of this measure is the elasticity of the labor supply curve facing the firm. With one exception, the existing evidence on monopsony is at an aggregate level (Sullivan 1989; Boal and Ransom 1997; Staiger, Spetz and Phibbs 2010; Hirsch, Schank and Schnabel 2010; Falch

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<sup>1</sup>The following empirical analysis deals with establishments that may or may not be a part of a larger corporation, but I will use the terms firm and establishment interchangeably.

<sup>2</sup>A true monopsony has only one buyer of a good, but I follow the recent literature and consider that term synonymous with monopsonistic competition, upward sloping labor supply curve to the firm, and labor market power (Manning 2003).

<sup>3</sup>This measure is similar to the Lerner Index used to measure product market power.

2010; Ransom and Sims 2010). The one exception is Ransom and Oaxaca (2010), whose data are from only one grocery store chain, so that their estimate is for the monopsony power of that one firm<sup>4</sup>.

In contrast, I build a method for calculating this measure of market power at the firm-year level. Using a panel of manufacturing establishments in Indonesia, I calculate the marginal revenue product of firms directly by evaluating the derivative of the firm's production function at their observed level of inputs. I then compare the marginal revenue product of labor to the wage each firm pays its workers to construct Pigou's measure of monopsonistic behavior. This direct approach for measuring monopsony has been used before, most notably in the labor market for professional baseball players (Scully 1974; Medoff 1976; Zimbalist 1992; Boal and Ransom 1997). However, this setting requires strong assumptions about how player productivity is linked to team revenue, and is not very representative of the general workforce. Earlier literature has also taken a similar approach to measuring labor market power, however the empirical work was either done for the US as a whole over time (Thurow 1968; Persky and Tsang 1974), or in a cross-section using only a handful of data points from major industry categories (Hildebrand and Liu 1965). The agricultural economics literature also directly compares the marginal revenue product of labor to wages, though estimating the productivity of workers on farms (Feder 1985; Binswanger and Rosenzweig 1986; Barrett et al 2008).

I build on these literatures by leveraging the rich literature that has emerged on how to reliably estimate production functions for firms (Olley and Pakes 1996; Blundell and Bond 1998, 2000; Akerberg, Caves, and Frazer 2006)<sup>5</sup>. Using Blundell and Bond's 'System GMM' estimator for reasons discussed in more detail below, I am able to consistently estimate each firm's marginal revenue product of labor, which I then use to construct a firm-year specific measurement of market power.

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<sup>4</sup>A recent working paper by Webber (2011) has estimated firm specific labor supply elasticities using the US Census Bureau's Longitudinal Employer Household Dynamics data set.

<sup>5</sup>Van Biesebroeck (2007) provides a useful summary of the various techniques.

After estimating the firm-year mark-down on wages, I provide evidence that this is indeed a measure of monopsony. I first test whether the measure is consistent with the traditional view of monopsony, that firms in highly concentrated labor markets have more market power than firms in less concentrated markets. Similarly, I test if firms with a higher share of employment in the local labor market have higher levels of market power. I also consider various alternative explanations, such as monopolistic exploitation, compensating differentials, and efficiency wages. While I can not prove that my measured gaps are solely due to labor market power, I argue that the measure is consistent with monopsonistic behavior.

Indonesia is a good setting to look for evidence of monopsonistic behavior, because the labor market frictions that lead to market power are more likely to occur there than in a developed country. The traditional basis for monopsonistic behavior is the existence of moving costs between labor markets. Indonesia has over 13,000 islands with many geographic and cultural barriers between them that make it difficult for workers to look for employment in another labor market. The more recent theories of monopsony are also based on frictions that are more prevalent in Indonesia (and many emerging economies). The search frictions underlying Burdett and Mortensen's model (1998) are based on imperfect information across workers and firms, and I do not think its too strong of an assumption that information flows less freely in developing countries. Another source of monopsony is firm differentiation which leads to different workers preferring to work for different types of firms. The difference in working environments between the large and small firms in Indonesia is significant because there are not as many standards the small firms need to comply with as there are in developed countries. There are also many types of firm owners that separate the labor market in Indonesia. Employees likely have preferences over working for a foreign owned firm or a domestic firm, and within each category there would be differences between US, Dutch, and Chinese foreign ownership, and between Javanese, Balinese, Chinese domestic ownership. Finally, one of the assumptions of the Burdett and Mortensen model is that firms have increasing recruiting costs (Kuhn 2004). While this may not be a natural assumption in

a developed country context, it is likely more prevalent in Indonesia as growing firms may quickly exhaust their network of friends and family and have to move to more costly recruiting practices. There is also anecdotal evidence of large manufacturing plants exhausting the local supply of a certain type of worker (say, with a high school diploma), and be forced to consider busing in workers from a different labor market, or invest in the capacity of the local education system.

In this paper, I find that over half of the manufacturing establishments in Indonesia have a significant amount of labor market power. The median level of market power is 1.67, which translates to a labor supply elasticity to the firm of 0.60. This is evidence of more labor market power and across a broader spectrum of firms than what has previously been found in the literature. I also show that labor market characteristics are important in explaining the variation in market power across firms and time, but not as important as firm characteristics.

These findings have several important implications. A person's labor is usually their most valuable asset (especially in a developing country), and formal sector employment is a common means for people to move out of poverty (La Porta and Shleifer 2008). Industrialization is generally viewed as the engine of growth that will pull millions of people out of poverty. Indeed, Indonesia's industrial sector has added approximately 15 million new jobs over the last 30 years<sup>6</sup>. However, the findings in this paper suggest that firms are behaving monopsonistically, which implies that fewer workers are employed and at lower wages than would be if firms were operating in competitive labor markets.

In addition, the technique developed here can be used in many contexts and for other purposes. I use a standard establishment level panel data set for the majority of the analysis. Such data are becoming increasingly available for many countries. The measure I develop here could also be used to refine our understanding of why firms respond differently to various policies. For example, theory predicts that firms with market power would respond differently to a policy that increases severance payments. Firms sourcing labor in a competitive market

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<sup>6</sup>Author's calculations based on World Bank's World Development Indicators.

would decrease employment and see an increase in total labor costs. However, as will be shown below, firms with market power are able to defray some of the increased costs and not have labor costs rise as much. Lastly, knowing whether market power is determined at the market level or individual firm level also impacts the policy discourse. For example, a common response to monopsonistic labor markets is a minimum wage policy. But if firms in the same labor market have different levels of market power, a market wide minimum wage policy will have mixed results, changing the overall cost-benefit analysis.

My work is also relevant to the recent studies looking at the differences in total factor productivity (TFP) across countries (Klenow and Rodriguez-Clare 2005; Rusticcia and Rogerson 2008; Hsieh and Klenow 2009). Klenow and Rodriguez-Clare examine how different rates of technology adoption affect the differences of TFP across countries. Both Rusticcia and Rogerson, and Hsieh and Klenow show that misallocation of resources across firms within a country affects the overall TFP. Firm level market power, of the kind studied in this paper, would lead to inefficient allocation of resources across firms and is an example of the distortions considered in these papers.

In the next section I provide a brief review of the relevant literature. Section 3 develops the empirical methods that will be used. Section 4 describes the Indonesian context and the data set. Section 5 presents the results on how prevalent monopsonistic behavior is among firms. Section 6 provides checks on my measure of monopsony and considers alternative explanations. Section 7 then analyzes the relative importance of firm specific and market characteristics in determining the market power of firms. Section 8 provides some robustness checks and considers an extension of this work. Section 9 then discusses policy implications and concludes.

## 2 Literature Review

It has long been known that firms pay different wages to similar workers (Krueger and Summers 1988; Davis and Haltiwanger 1991; Abowd, Kramarz, and Margolis 1999), which suggests that firms are not sourcing labor from a competitive labor market. Many studies have indeed found evidence for monopsonistic behavior in specific labor markets in developed countries. Boal and Ransom (1997) provide a nice summary, and a recent volume of the *Journal of Labor Economics* (April 2010) was dedicated to work on the evidence for monopsony. Most of the studies look for monopsony by estimating the labor supply elasticity to the firm. One way to estimate this elasticity is to regress log employment on log wages with various controls (or vice versa). Since firms choose labor and wages simultaneously, this approach is identified through the use of firm level instruments that affect wages without impacting employment. Examples of this approach include Sullivan's study of nurses (1989), Boal's study of coal-mining towns in West Virginia (1995), Staiger, Spetz, and Phibbs' study of nurses (2010), and Matsudaira's study of the low wage health care market in California (2010) among others.

A good example of this approach is Staiger, Spetz and Phibbs (2010) who use a government mandated change in the wages of registered nurses at Veteran Affairs (VA) hospitals as their exogenous variation. They derive the labor supply equation facing each hospital as a function of its own wage and the wages of its two nearest competitors. They then estimate the elasticity of the labor supply curve directly and instrument for the difference in wages between the hospital and its two nearest competitors by using the VA / non-VA status of the hospital. They find significant evidence of monopsony, with the short-run elasticity of the labor supply curve to individual hospitals being 0.1 on average.

This is striking evidence, as other studies of the nursing market have found smaller amounts of market power or none at all. There is some debate about the size of Sullivan's findings (1989), with Sullivan originally stating that the nurses were paid between 43% (for one year changes) and 21% (for three year changes) below marginal product. However, Boal

and Ransom (1997) reinterpret Sullivan's findings in a dynamic context and characterize his findings as implying wages being between 87 and 96% of marginal product, indicating little market power. Matsudaira (2010) also looks at the health care industry, focusing on nurses and nursing aides in the long-term care industry of California. Using a law change mandating a minimum number of staff per resident as a natural experiment, he finds little evidence of monopsony in the market for nurses, and significant evidence of no monopsony in the labor market for nursing aides. He suggests that the market for nursing aides could be competitive because there is little formal training required to become a nursing aide, allowing for supply to increase easily, and because there are more nursing homes than there are hospitals, leading to more competition between employers.

The other primary method for estimating the labor supply elasticity to an individual firm is a dynamic approach proposed by Manning (2003), based on Burdett and Mortensen's (1998) model of job search. Manning estimates the elasticity of the labor supply curve to a firm as a function of the firm's separation and recruitment rates. He shows that the labor supply elasticity can be estimated as a function of the separation elasticity to employment, the separation elasticity to unemployment, and the share of recruits from employment. Hirsch, Schank, and Schnabel (2010) use this approach to show that men have more elastic labor supply curves than women using a matched employer-employee data set from Germany. The difference in labor supply elasticities explains about a third of the gender pay gap, as monopsonistic employers discriminate against women. Moreover, Hirsch et al. find average labor supply elasticities to the firm in the range of 1.9 to 3.7, which is evidence that firms do have market power. Ransom and Sims (2010) also used this dynamic approach to study the labor market for teachers in Missouri, and find estimates for the labor supply elasticity to the firm of about 3.7.

All of the above studies have generated estimates of market power at an aggregate level. However, one recent study has used the dynamic approach for estimating monopsony to derive firm specific measures of market power. Ransom and Oaxaca (2010) find that men



and women have different labor supply elasticities to a specific grocery store chain in the Southwest United States. They find that male labor supply elasticities to the firm in the range of 2.4 - 3.0, and female labor supply elasticities between 1.5 - 2.5. I build on this work by developing a firm specific measure for monopsony that has broader coverage than that used by Ransom and Oaxaca, and is from a more pressing context as developing countries generally have lower levels of labor regulation and worker protection.

In addition to the studies looking for evidence of monopsony, my work builds on the literature that has compared the marginal revenue products of workers to the wages they are paid. Some of the first empirical studies to do so did the best they could with the limited data available at the time. Hildebrand and Liu (1965) use the Annual Survey of Manufactures from 1957 to thoroughly study manufacturing production functions. They estimate Cobb-Douglas production functions separately by industry, finding that labor is paid between 58% and 115% of its marginal product across industries<sup>7</sup>. Thurow (1968) estimates production functions using time series data for the United States as a whole from 1929-1965, and finds that labor is paid between 56 and 65% of their marginal product. Perskey and Tsang (1975) use 35 years of aggregate US data to study the determinates of labor market power. They find that unionization decreases market power, whereas unemployment, inflation, and growth in capital stock all work to increase labor market power.

In their comprehensive review, Boal and Ransom (1997) discuss another series of studies that directly compare the marginal revenue product of a firm to its wage, all using professional baseball in the United States as their context (Scully 1974; Medoff 1976; Zimbalist 1992). Baseball is a useful context because it is an oligopsonist organization and there is good data on the productivity of individual labor. However, strong assumptions are needed to link that productivity to each teams' revenue, arguing that revenue is only increased through more wins. These studies find a range for the elasticity of labor supply between 0.14 and 1.

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<sup>7</sup>The top end of that range is for the Transportation Equipment industry, and is the only estimate above 100%.

The agricultural economics literature has also estimated the MRPL of workers, but for workers on farms. This literature has found that households do not allocate labor as competitive theory would predict,  $MRPL = W$  (Binswanger and Rosenzweig 1986; Udry 1996; Barrett, Sherlund, and Adesina 2008). Udry uses a detailed agricultural panel to show that households do not equalize labor productivities across plots farmed by men and women, even controlling for detailed plot characteristics and type of crop planted. Barrett et al. find that households do not equalize marginal revenue products of labor to their shadow wages, and uses that inefficiency in the structural estimation of the households' labor supply decisions.

There has been at least one other paper to investigate whether market power was determined more at the firm or market level (Hirsch and Schumacher 2005). Using the nursing market in the US as their context, the authors do not find evidence for market determined monopsonistic behavior in the short run, nor do they find evidence of firm level monopsony. I build on this work by employing a more direct measure of monopsony, examining a context where monopsonistic behavior is more likely to occur, and by looking at a broader set of occupations.

This research also adds to the literature analyzing how firms respond to policy changes. For example, consider the large literature on how a minimum wage policy impacts the labor market. There is mixed evidence for the United States with Neumark and Wascher (2008) finding negative employment effects of minimum wage policies, Dube, Lester, and Reich (2010) finding no negative effects, and Card and Krueger (1994) famously finding positive effects. There have been some recent studies in the developing country context that have found that minimum wages can increase wages, although sometimes with negative employment effects (Gindling and Terrell 2005, 2010; Alatas and Cameron 2009). It could be that firms have different levels of market power which would impact how they respond to the minimum wage policy. Theory predicts that firms with market power would increase both employment and wages in response to a minimum wage (if the minimum is set above the firms' current wage and below their current marginal revenue product), whereas compet-

itive firms would decrease employment. Another example of how monopsonistic behavior mitigates a firm's response to a policy change is considered within this paper. Later on, I develop predictions showing that firms with market power should have smaller responses in both wages and employment to a mandated increase in firing restrictions as compared to competitive firms.

### 3 Empirical Approach

#### 3.1 Constructing the Measure of Market Power

Joan Robinson is credited with first discussing the idea of imperfect competition in labor markets (1933). This analysis has been incorporated into many introductory economics textbooks and is the complement of the standard monopoly treatment. This static treatment of monopsony says that firms will set wages where  $R'(L) = W(L) + W'(L)L$ , with  $R'(L)$  being the marginal revenue product of labor, and the right hand side is the marginal cost of labor with  $W(L)$  being the inverse labor supply curve. The difference between this condition and the classic competitive treatment is that the wage is a function of labor,  $L$ , and not constant. From here, Pigou's measure of monopsonistic behavior is given as:

$$E = \frac{R'(L) - W(L)}{W(L)}. \tag{1}$$

It is easy to show that  $E = \epsilon^{-1}$ , where  $\epsilon$  is the elasticity of the labor supply curve<sup>8</sup>. In the competitive framework, firms hire up to the point where  $R'(L) = W$ , which implies that Pigou's measure would be equal to zero, and the elasticity would be infinity. If firms are behaving monopsonistically,  $W'(L)L > 0$  and then Pigou's measure is strictly positive.

Since it is common for establishment data to have information on wages paid to workers,

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<sup>8</sup>Let  $\epsilon = \frac{WL'(W)}{L(W)}$ . Substitute the first order condition for wages into the equation for  $E$  to get  $E = \frac{W'(L)L}{W(L)} = \epsilon^{-1}$

the key step in generating this measure of market power is to develop a credible estimate for the marginal revenue product of labor (MRPL) for firms. The general idea of the approach used in this paper is to estimate a firm’s production function and then evaluate the derivative of the production function at each firms’ current levels of revenue and employment to get a firm-year specific measure of MRPL. To estimate the production function, I use methods based on Blundell and Bond’s System GMM estimator for dynamic panel data models (1998, 2000). I will briefly explain the standard approach for estimating production functions, and then explain why its necessary to use the dynamic panel data method for this analysis.

The literature often represents the production function of a firm with a Cobb-Douglas specification or a transcendental-logarithmic (trans-log) form. I consider the trans-log form in the empirical work below, and focus on the Cobb-Douglas specification here for clarity. The Cobb-Douglas takes the form,  $Y_{it} = AL_{it}^{\beta_L} K_{it}^{\beta_K}$ , where  $Y_{it}$  is the output of firm  $i$  at time  $t$ ,  $L_{it}$  is the amount of labor used in production,  $K_{it}$  is capital, and  $A$  is total factor productivity<sup>9</sup>.  $\beta_j$  is the factor share of factor  $j \in \{L, K\}$ . The most direct way to estimate this is to convert it to logs and estimate the equation:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \epsilon_{it}, \tag{2}$$

where the lowercase letters represent the log version of the variable and the constant term is subsumed into the error term. An OLS estimate of this equation will lead to biased results as there are factors unobserved to the econometrician that affect both the firm’s choice of inputs and the firm’s output. These factors are most often described as firm specific productivity and incorporated into the model as:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \omega_{it} + \nu_{it}, \tag{3}$$

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<sup>9</sup>My empirical work considers two types of labor, intermediate inputs, and capital as inputs into the production function, but I focus on just two inputs here for clarity.

with  $\omega_{it}$  representing firm-specific productivity and  $\nu_{it}$  capturing any measurement error or optimization errors on the part of the firm. A standard way to estimate this equation was developed by Olley and Pakes (1996), who made assumptions about the timing of the evolution of productivity, capital and labor. The authors used the investment of the firm to break the endogeneity between capital and productivity, arguing that the investment decisions were made prior to the realization of the current productivity shock. Levinsohn and Petrin (2003) extended this work by noting that firm-level data sets often had missing values for investment causing those observations to drop out of the estimation. Instead, they proposed that materials could be used to break the endogeneity of productivity. Recently, Akerberg, Caves, and Frazer (2006) noted that both Olley-Pakes (OP) and the Levinsohn-Petrin (LP) approaches suffer from collinearity because labor is chosen by the firm in a similar manner as investment (or materials), as functions of capital and productivity. The first stage of OP and LP can then not identify both the coefficient on labor and the non-parametric relationship between output and capital and investment and are therefore collinear. Their solution is to assume that capital is more fixed than labor, which is more fixed than investment (or materials). Productivity evolves according to a first-order Markov process between each decision point, leading to moment conditions which identify the parameters of the production function. However, this approach does not allow for firms to hire labor monopsonistically, which makes the choice of labor endogenous with the error term.

The most direct way to deal with this new form of endogeneity in the production function is to instrument for the choice of labor. This naturally leads to another main approach for estimating production functions, that of Blundell and Bond, which generates instruments from within the data itself. Their technique is based on the work of Anderson and Hsiao (1982) and Arellano and Bond (1991), who used lagged variables as instruments for first differences of panel data. Blundell and Bond (1998, 2000) build on this by adding instruments for current levels with lagged differences, and combining both sets of instruments into a system, hence the name System GMM.

Akerberg, Caves and Frazer provide a useful comparison of the two approaches. In the Olley-Pakes strand of approaches, productivity follows a first-order Markov process, whereas in Blundell-Bond, productivity evolves linearly in an AR(1) process,  $\omega_{it} = \rho\omega_{it-1} + \eta_{it}$ . While the Blundell-Bond assumption is more restrictive, it is the linearity of the AR(1) process that provides a moment condition used in estimation. A second difference is that Blundell-Bond allows for firm fixed effects, which are used to capture unobserved firm characteristics that stay constant over time. The Blundell-Bond approach also requires fewer assumptions regarding the input demand equations. The Olley-Pakes based approaches require that productivity be strictly increasing in the proxy variable (investment or materials), and also that there are no other factors influencing productivity besides capital and the proxy variable.

Van Biesebrock (2007) provides a good overview of many ways to estimate production functions and argues that Blundell and Bond's system GMM estimator yields robust estimates when technology is heterogenous across firms and there is a lot of measurement error in the data, or if some of the productivity differences are constant across time. He also argues that if firms are subject to idiosyncratic productivity shocks that are not entirely transitory, then the Olley-Pakes' estimators will be more efficient.

I use the Blundell-Bond estimator for three reasons. First, the data set lacks a reliable instrument for employment, which is necessary in order to implement the Olley-Pakes based approaches in the presence of monopsony. The Blundell-Bond approach provides the necessary instrumental variables. Second, because Indonesia is an emerging economy, there are likely large fixed differences in the unobserved qualities of firms, which suggests that firm fixed effects are important. Third, the Blundell-Bond estimator is considered to be more robust to measurement error (Van Biesebrock 2007), which is always a concern with large firm-level data sets from developing countries. While I use the Blundell and Bond estimator for my main results, I also check the robustness of my results using the Akerberg, Caves, and Frazer technique, instrumenting for the endogenous choice of labor with the concentration ratio of the local labor market.

The Blundell-Bond technique estimates a dynamic production function that takes on the reduced form of

$$y_{it} = \rho y_{it-1} + \beta_L(l_{it} - \rho l_{it-1}) + \beta_K(k_{it} - \rho k_{it-1}) + (\gamma_t - \rho \gamma_{t-1}) + (\delta_i(1 - \rho)\eta_{it} + \nu_{it} + \rho \nu_{it-1}) \quad (4)$$

where  $\gamma_t$  is a year fixed effect,  $\delta_i$  is a firm fixed effect, and  $\rho$  is the autocorrelation coefficient. I follow Roodman (2006) and estimate this equation in a two-step GMM procedure. The first step is used to build an optimal weighting matrix which is then used to make the second step efficient. I use forward-orthogonal deviations instead of first differences to minimize sample loss due to gaps in the panel. This procedure subtracts the average of all available future observations instead of differencing with the previous one. System GMM also has the ability to generate many instruments, though I limit this by just using the lags from 2 and 3 periods previous and by collapsing the instruments from the different lag lengths into one moment.

I then recover the structural parameters using standard minimum distance techniques. The five reduced form parameters constitute the vector  $\hat{\pi}$ , and the three structural parameters  $(\beta_L, \beta_K, \rho) = \hat{\theta}$ . After representing the mapping between the two vectors as  $h()$ , I can represent the minimization problem as:

$$\min_{\theta \in \Theta} \{\hat{\pi} - h(\theta)\}' \hat{\Xi}^{-1} \{\hat{\pi} - h(\theta)\}, \quad (5)$$

where  $\hat{\Xi}$  is the efficient weighting matrix, which is the asymptotic variance of the first stage estimates,  $avar(\hat{\pi})$ . Then, to obtain the asymptotic variance of the estimates, I take the Jacobian of  $h()$  and represent it as  $\hat{H}$ , and then we have:

$$AsyVar(\hat{\theta}) = \frac{1}{n} [\hat{H}' \hat{\Xi}^{-1} \hat{H}]^{-1} \quad (6)$$

$$= (\hat{H}' [avar(\hat{\pi})]^{-1} \hat{H})^{-1}. \quad (7)$$

This process generates estimates for the parameters of the production function. The above process assumes that all firms in the estimation sample share the same technology, in that I only estimate one  $\beta_L$ . To weaken the impact of this assumption, I estimate the production function separately by four-digit industries<sup>10</sup>. I also check the validity of this assumption by estimating the more flexible transcendental-logarithmic function. The trans-log production function takes the form,

$$y_{it} = \beta_0 + \sum_N \beta_N \ln(N_{it}) + (1/2) \sum_N \sum_Q \beta_{NQ} \ln(N_{it}) \ln(Q_{it}), \quad (8)$$

for each  $N, Q \in [L_{PR}, L_{NP}, K, M]$ . The Cobb-Douglas production function is nested within this formulation, and an F-test can be conducted on the extra parameters to determine if they are jointly significantly different from zero. When estimating this form separately by four-digit industry, the extra parameters (not used in the Cobb-Douglas form) are not significantly different from zero in 82 of the 83 industries. Since the trans-log form puts more stress on the data, requiring more observations, I also estimate the production function separately by two-digit industry. In this case, 17 of the 19 industries reject the extra trans-log parameters. These results lend more credence to the use of the Cobb-Douglas production function in the main analysis.

With these industry specific estimates for the parameters of the Cobb-Douglas production function, I then generate firm-year specific measures for the marginal revenue product of each firm as

$$MRPL_{it} = \frac{\partial Y_{it}}{\partial L_{it}} = \frac{\hat{\beta}_{L_j} Y_{it}}{L_{it}}, \quad (9)$$

for firm  $i$ , year  $t$ , and industry  $j$ . It is then straightforward to calculate the firm-year specific measure of market power from equation (1).

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<sup>10</sup>As a robustness check, I estimate the production function separately by two-digit industries and find the main results are unchanged.



## 3.2 Testing the Measure of Market Power

Using the measure of market power, I perform two tests to see if it behaves in a manner that is consistent with monopsony. I check if the measure is related to labor market concentration at both a firm and market level as traditional theory would predict. I then also consider alternative explanations for the wage being below the marginal revenue product of labor.

Traditional theory of monopsony predicts that firms who control a large share of the market are able to move the price. Therefore, the larger share of total employment that an individual firm employs should be positively correlated with market power. Each firm's employment share is the ratio of their employment to the total level of employment in their labor market.

A similar test can be conducted at the market level. Firms in labor markets where workers do not have many other options should have more market power than firms in labor markets where workers have many alternative employers readily available. The number of alternative options is formalized in measures of concentration of the labor market, which increases as the labor markets become more sparse. A necessary condition for monopsony is that measures of labor market concentration are positively correlated with the estimated firm-level market power.

The measure of market concentration I use is the concentration ratio of the eight largest firms in the labor market. This is calculated by summing the market shares of the eight largest firms in the labor market. The key, as with all measures of market concentration, is how to define the labor market. Here, I use geographic districts. This assumes that a production worker employed by a local furniture manufacturer could also work for the local garment manufacturer. Indonesia has almost 400 districts across the country, so its plausible that workers would be willing to move to another job in the same district as its not that far away. However, this definition does assume that the skills of workers are able to cross industries, which might not always be the case.

There are also other potential explanations for the wedge between marginal revenue product of labor and wages, I consider whether monopolistic competition, compensating differentials, or efficiency wages may lead to a firm not paying wages equal to the marginal revenue product of workers. I am able to control for these competing explanations with the nature of my data and method.

At the root of Pigou's measure of market is a gap between the marginal revenue product of the worker and the wage the firm pays the worker. The monopsonistic explanation for this gap depends on there being an upward sloping labor supply curve to the firm. However, if a firm is a monopolist in the product market and operating in a competitive labor market, Robinson (1933) has shown that the firm will not pay workers the full value of their production. The key difference in this situation is that the monopolist has a 'value of the marginal product' ( $P \cdot MP$ ) that is different from the marginal revenue product of labor. This is because the additional output generated by the marginal worker will reduce the output price of the monopolist, lowering the marginal revenue generated. This monopolistic exploitation of the workers is distinct from the inefficiency I measure in this paper since my method estimates the marginal revenue product of labor directly. Any monopolistic exploitation that occurs is above and beyond the wage mark-down I measure in this paper.

Compensating differentials are another explanation for why a firm might not pay a worker their marginal revenue product. Here, the firm is still trying to set their total labor costs equal to the marginal revenue product of labor, but some of the labor costs are not in the form of wages. To the extent that these extra benefits are pecuniary, my measure is not biased as my data has information on both wages and benefits paid to workers. However, there may be other non-pecuniary factors that influences the wages paid to workers. These could be the riskiness of the job, the cleanliness of the workplace, or the quality of the co-workers. If workers took less pay to work in exchange for some of these benefits, their marginal revenue product would not equal their wage. This only biases my results if all workers have the same prices for these non-pecuniary attributes. If workers have different prices, which is a more

realistic assumption, then the labor supply curve to the firm is upward sloping as the firm needs to pay higher wages to attract the next worker who has a marginally lower valuation of that firm's working conditions.

Efficiency wages are often used to explain wage variation across firms, as some firms find it profitable to pay above market wages. Yet, to the extent the same efficiency wage is paid to all workers in a particular firm, this will not affect my analysis as the firm will still set the marginal revenue product of labor equal to the wage. And since efficiency wages are actually paid to the workers, they will be observed in my data as actual wages. The efficiency wage may be different from the market wage, but my analysis makes no assumptions about the market wage.

This discussion does not conclusively demonstrate that the mark-down I measure is solely due to monopsonistic behavior on the part of the firm, but shows that the measure is consistent with firms having labor market power.

### 3.3 Separating Influences of Market Power

With a measure of market power for each firm-year observation, I am able to separate the within-labor market variation from the between labor market variation in market power. To do this I will generate partial correlation coefficients for different sets of independent variables. The partial correlation coefficient for an independent variable,  $X$ , captures how much of the overall variation in the dependent variable can be explained by  $X$ . To calculate the partial correlation coefficient for a variable or set of variables,  $X$ , I first get the  $R^2$  from the model with all of the controls and the  $R_X^2$  from the model with  $X$  excluded. Then the partial coefficient is formulated as  $\rho_X = (R^2 - R_X^2)/(1 - R_X^2)$ . If the partial correlation coefficient for the labor market controls is larger than the value for that of the firm controls, then the labor market determines more of the variation in market power than do the individual firm characteristics (or vice versa).

To control for labor market variation, I will use a measure of concentration for the

labor market and the local unemployment rate. The concentration ratio varies over time and represents the traditional view of how labor markets influence market power. As local unemployment increases, firms in that labor market should be able to pay lower wages as there are more workers available for any given job. I will also include labor market fixed effects which will control for any differences in the labor markets that stay constant over time. For example, this will capture any market-specific moving costs due to language barriers or other distinct features of areas within Indonesia.

To control for firm-level characteristics that may impact market power, I include controls for firm age, foreign ownership, output growth, firm size, and product market concentration. Firm age could lead to more market power as workers prefer to work for more stable employers. But workers may also prefer to work for younger firms that tend to be more dynamic, with more growth potential, so the sign on firm age could go either way. I also control for growth by including a measure of one-year output growth. Foreign owned firms might be expected to have less labor market power as they are unfamiliar with the local customs and practices, but that would just increase their recruiting costs, and not influence their market power. However, if workers prefer to work for foreign firms, they would have increased market power. Firm size may also affect product market power, and I use capital to proxy for firm size<sup>11</sup>. Product market power should not be mechanically correlated with labor market power (as previously explained), but the monopolist firm may have a more secure future which is more attractive to potential workers. In addition, I will include firm fixed effects, which control for any time-invariant firm characteristics that influence market power. These could be working conditions that differ across firms, but are not captured in the total labor costs I use when constructing the measure of market power.

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<sup>11</sup>I can not use output or employment for firm size, as those variables are used directly in the computation of Pigou's E.

## 4 Data

The data for this paper come from the Indonesia Annual Manufacturing Survey, *Survei Tahunan Perusahaan Industri Pengolahan* (SI). It is a census of all the manufacturing establishments in Indonesia with at least 20 employees. Firms are required to fill out the survey each year, and the dataset covers years 1988-2006. Among the substantial number of variables in the dataset are the following which I use in this study: output (revenue), intermediate inputs, investment, capital, wages, non-wage compensation, number of employees, ownership, location, industry, etc.

To construct an average wage measure for each firm, I add total wages to total benefits, and then divide by the number of employees in each firm. I repeat this step for production and non-production workers, to get the average wage for each type of worker. Since prices are different for consumers than they are for industries, I deflate wages using Indonesia's consumer price index to constant 2000 Rupiah and I deflate all other monetary values using industry specific wholesale price indices to constant 2000 Rupiah. The exchange rate in the year 2000 was about 8,400 Rupiah to 1 US Dollar. The question in the survey on establishment ownership asks how much of the firm's capital is owned by the local government, central government, foreign interests, or private interests. I follow the standard practice of considering a firm to be foreign-owned if at least 10% of its capital is foreign owned.

I performed some basic data cleaning procedures following other studies that have used the Indonesian SI data (Blalock and Gertler 2004, Hallward-Driemeier and Rijkers 2010). This included correcting for invalid values, missing values, and outliers. See Hallward-Driemeier and Rijkers (2010) for details. I present results using the raw data in the robustness section and find similar results to the ones presented in the text below.

Summary statistics for the data can be found in Table 1. Each observation is a firm-year. Firms are on average 14.5 years old, which is different from the average number of years of data I have for each firm, 12.4. Firms have on average 192 employees, with about 84% of them working as production workers (as opposed to non-production, or white-collar workers).

Production workers make on average 4,261,000 rupiah/year, which is about US\$506 (in year 2000 dollars). The non-production workers earn over twice as much.

## 5 Market Power Results

In this section I will present results for the amount of market power establishments have in Indonesia using my new technique for measuring market power. The data provide information on both production workers and non-production workers. Hammermesh (1993) notes that the substitutability between the two types of workers is fairly low. Ehrenberg and Smith (2006) also show that workers with more education search across a wider labor market. These findings suggest that production and non-production workers participate in separate labor markets. I therefore estimate the production functions using each type of labor as a separate input. I also include intermediate inputs as a separate input in the production function. The resulting Cobb-Douglas model that I estimate is,

$$y_{it} = \beta_{L_{PR}} l_{it}^{PR} + \rho \beta_{L_{PR}} l_{it-1}^{PR} + \beta_{L_{NP}} l_{it}^{NP} + \rho \beta_{L_{NP}} l_{it-1}^{NP} + \beta_K k_{it} + \rho \beta_K k_{it-1} + \beta_M m_{it} + \rho \beta_M m_{it-1} + \rho y_{it-1} + \delta_i + \mu_{it}, \quad (10)$$

where  $l^{PR}$  is the natural log of production employment,  $l^{NP}$  is the natural log of the non-production employment,  $k$  is the natural log of capital, and  $m$  is the natural log of the intermediate inputs used by firm  $i$  at time  $t$ .

There are a couple of econometric concerns that are important to consider when using the System-GMM technique. The technique has the potential to generate numerous instruments, which can overfit endogenous variables. Windmeijer (2005) tests the importance of the number of instruments, and provides a rule of thumb suggesting the number of instruments should be less than the number of groups (which in this analysis is firms). I use the over-identifying restrictions to test for the validity of the instruments by using Hansen's test (1982). I also check for auto-correlation in the error following Arellano-Bond (1991), the presence of which would indicate the instruments were not exogenous.

Table 2 presents the results of estimating a Cobb-Douglas production function using Blundell and Bond's System GMM estimator with a reduced number of instruments. The estimated parameters of the production function are presented for 30 of the 83 industries on the left side of the table, and the specification tests are reported on the right side of the table. The raw averages for the values are reported in the last row of the table. In the column reporting the t-test of Constant Returns to Scale (CRS), none of the industries are estimated to be significantly different from CRS, and this is true for all of the industries. Some of the coefficients are estimated to be negative, but these observations are excluded from the analysis. Another check on the credibility of these estimates is to compare them to the actual factor shares. The raw average of the coefficients across all the industries is reported in the last row of Table 2. The corresponding factor shares are 0.19, 0.05, 0.08, and 0.68 respectively. While the capital coefficient is smaller than its factor share, the numbers are reasonably close overall.

The first two columns on the right side of the table check if there are enough firms in each estimation sample. I pass Windmeijer's rule of thumb in all industries. Looking at the Hansen test of the over-identifying restrictions for each industry, it should be noted that with the large number of instruments being used, the test can report incredibly high values, and so I exclude industries with P-values over 0.98. In 76 of the 83 industries, I pass Hansen's test for the validity of the instruments, though there are a few industries where the instruments are not valid, with P-values near zero. Finally, in the last two columns, the P-values for the auto-correlation tests of the error-term are reported. First-order auto-correlation of the differences is expected as the instrument and the error share a common term. The key test is whether there is second-order correlation in differences, presence of which would indicate that my instruments are invalid. The estimates for all of the industries but nine pass this test.

Taking all of these specification tests into account, the continued analysis will focus on firms in industries that pass all of the specification tests. From the original 306,217 firm-

year observations, 241,093 passed all of the specification tests (78.7%). Table 3 compares the means of the firms that passed all of the specification tests to the firms in industries that did not pass at least one test.

The first two columns of Table 3 report the means and standard deviations for the firms in industries that passed all of the specification tests. Columns (3) and (4) display the means and standard deviations for the excluded sample. The last column displays the t-test for equality of means between the two samples. There are quite a few differences across the two groups. The firms that are excluded tend to be smaller, older, and export less on average. They pay slightly lower wages, and also are in labor markets that are more concentrated. While all of the following analyses are appropriately specified, the results may not be fully representative of the broader population of firms in Indonesia.

With the estimates for the parameters of the production function, I am able to calculate the marginal revenue product of labor for each type of worker separately. The Cobb-Douglas revenue-production function for each firm is

$$Y = A(L_{PR})^{\beta_{LPR}}(L_{NP})^{\beta_{LNP}}K^{\beta_K}M^{\beta_M},$$

with  $L_{PR}$  being the number of production workers in the firm and  $L_{NP}$  being the number of non-production workers. The marginal revenue product for each type of worker is then,

$$\frac{\partial Y}{\partial L_{PR}} = \frac{\hat{\beta}_{L_{PR}}Y}{L_{PR}} \quad (11)$$

$$\frac{\partial Y}{\partial L_{NP}} = \frac{\hat{\beta}_{L_{NP}}Y}{L_{NP}} \quad (12)$$

As indicated above, Pigou's measure of market power can then be calculated separately for production and non-production workers using the average wage the firm pays to a worker of each type by the formula  $(MRPL_l - W_l)/W_l$  for each  $l \in (PR, NP)$ .

Table 4 presents the results for Pigou's measure of market power. The top two lines



of the table show the results for the production workers and the bottom two for the non-production workers. Column (2) presents the mean of market power, weighted by the number of employees in each firm. Columns (3) displays the median of the distribution, and then columns (4) - (6) display the percentage of observations that lie in three ranges. Column (4) consists of firms with measures of Pigou's E below 0.33, which suggests that the firms have little to no market power. The value of 0.33 is not an exact cutoff, but indicates that the workers' MRPL is only 33% above their wage. Ideally, a competitive firm would pay wages equal to the marginal revenue product of labor, which would yield a value for E of zero. Column (5) has firms with measures of Pigou's E between 0.33 and 2, which suggests that they have some market power. The value of 2 for Pigou's E indicates that workers' MRPL is three times higher than their wage. The last column is for firms with a lot of market power, having measures greater than 2.

Table 4 reports the values for Pigou's E and shows that many firms have market power, though there is variation in market power across firms. The main results are presented in the first row, and show that the median firm has a value of Pigou's E equal to 1.93, which is equivalent to a labor supply elasticity to the firm of 0.52. The categories show that 40% of firms have little to no market power, whereas 28% have some market power, and about 31% have a lot of market power. To my knowledge, this is the first estimate for the monopsonistic behavior of firms in an emerging economy, and also the first to show the distribution of market power across firms. While the median firm has more market power than most of the previous estimates in the literature, it is not the biggest.

Comparing the top and bottom panels shows that there are more firms with a lot of market power over non-production workers than firms with market power over production workers. This suggests that non-production workers are less mobile and not as able to find alternative jobs, while the production workers are more mobile. This could be due to non-production jobs requiring more firm specific human capital, preventing non-production workers from having a lot of alternative jobs they could switch to. However, these results are

suspect because there is a wide variety of worker quality within the non-production category, and my method assumes that all workers in each category have the same productive ability. For this reason, and because the production workers comprise the vast majority of the workforce, I will focus the rest of the analysis on the production workers.

## 6 Testing the Measure of Market Power

Table 5 reports the results of two tests of whether the measure of market power I have calculated is consistent with the traditional understanding of monopsony. The first two columns check if firms that employ a higher share of labor in their local labor market have more market power. The last two columns check whether firms in more concentrated labor markets have more market power. I use the natural log of the measure of market power as the dependent variable, and since some of the firms have values of market power below zero, I add a value of one to each observation prior to taking the natural log<sup>12</sup>.

The first column in Table 5 shows the results of a GLS regression using the firm's labor market share as the primary control variable, and also year, industry, and region dummies. The coefficient is positive and significant, as the traditional view of monopsony predicts. The second column includes other controls that could influence how much market power a firm has. The coefficient on the firm's market share remains positive and significant.

The last two columns check whether market power is positively correlated with market concentration. I allow market concentration to affect market power non-linearly, creating dummy variables for firms in markets with low and high levels of market concentration. I define low and high as the firms in the lowest and highest quartiles of market concentration. The firms with medium levels of concentration are the omitted category. The results do show that firms in labor markets with low levels of concentration have less market power. The coefficient on the highly concentrated labor markets is positive, as theory would predict,

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<sup>12</sup>The minimum value possible for Pigou's E is -1 since the marginal revenue product of labor is constrained to be positive.

but is not statistically significant in either specification.

The results of these tests support my claim that this measure of market power is consistent with monopsonistic behavior. Another check is considered in the extension section below. There, I develop predictions for how firms with market power would respond differently to an increase in firing restrictions than firms in competitive labor markets. Upon testing these predictions, I find results consistent with the predictions, providing more support that the measure I calculate is capturing the monopsonistic behavior of firms.

## 7 Separating Influences of Market Power

The previous literature has documented the existence of market power in some labor markets, though it was not able to separate whether the market power is a characteristic of the labor market or if firms within the same labor market can have different levels of monopsony power. In this section, I take the individual firm-year measurements of market power that I have produced and regress those on various firm and market characteristics to see which factors influence market power more. I do this for production workers using a simple Generalized Least Squares (GLS) model by systematically adding the various controls<sup>13</sup>. Using the log of Pigou’s measure of market power,  $e_{ijt} = \ln(E_{ijt})$ , for firm  $i$  in labor market  $j$  at time  $t$ , as the dependent variable. The model I estimate is

$$e_{ijt} = \alpha_0 + \mathbf{X}_{it}\alpha_1 + \mathbf{Y}_{jt}\alpha_2 + \gamma_j + \nu_i + \epsilon_{ijt}, \quad (13)$$

with  $\mathbf{X}_{it}$  being a set of time-varying firm characteristics,  $\mathbf{Y}_{jt}$  a set of time-varying labor market characteristics,  $\gamma_j$  a labor market fixed effect, and  $\nu_i$  capturing the firm fixed effects.

Based on the traditional economic theory of monopsony, I use the concentration ratio of the eight largest employers in the labor market as a time-varying labor market control.

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<sup>13</sup>I use feasible-GLS because its a more efficient estimator than OLS, giving more weight to observations with lower variance.

I also include the local unemployment rate as a measure of labor market slackness. This measure is calculated from Indonesia's labor force survey, Sakernas, though I only have this data for years 1990-2006<sup>14</sup>. The more recent theoretical developments also suggest what the appropriate firm controls should be. Firm differentiation can lead to market power, suggesting that firm characteristics impacting workers' perceptions of the firm should be controlled for. Here, I use the age of the firm, an indicator of whether the firm is foreign owned, and a measure of firm size. I use capital as a proxy for firm size as both output and employment are directly used in the construction of the market power measure. Schmieder (2010) has also shown that new firms are a good place to find evidence of monopsonistic behavior since they are hiring a lot of workers, and therefore contend with the upward sloping labor supply curve more. Since I already control for firm age, I include an additional control of one-year output growth to capture the firms that are growing.

As mentioned above, product market power is not mechanically linked to the measure of labor market power used here. However, workers may prefer to work for monopolistic firms as they may have a more secure future. To test for this, I calculate the Herfindahl-Hirschman Index for the product market by 2-digit industries within each province.

Table 6 presents the results of these GLS models where the controls have been entered systematically to enable the calculation of partial correlation coefficients for each group of controls. In the models without firm fixed effects, the standard errors are clustered at the labor market level to account for the correlation among the firms within the same labor market. Industry and year dummies are included in all models to control for any factors that are constant across all firms in the same year or industry, respectively. All models are weighted by the number of production employees at each firm.

I consider three models using various sets of the fixed effects. All of the models include industry and year dummies, whereas the second model includes the labor market fixed effects (local district), and the last model adds the firm fixed effects. The even numbered columns

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<sup>14</sup>I drop 1988 and 1989 from this stage of the analysis.

report the partial correlation coefficients for each group of controls.

Column (1) includes all of the time varying controls, but neither the market nor firm fixed effects. Firm in labor markets with low levels of concentration do have less labor market power. The coefficients on the other two controls are not statistically significant.

Looking at the firm specific characteristics, the age of the firm is not significantly related to market power, though both the foreign ownership of the firm and the output growth are statistically significant. The coefficients on foreign ownership and output growth suggest that foreign owned-growing firms have more market power, though the coefficient on output growth is small. Neither of the measures of product market concentration are statistically significant, however the proxy for firm size is positively correlated with market power.

The overall amount of variation explained by this model, using the adjusted  $R^2$ , is 0.276. About 1% of this variation can be explained by labor market characteristics, whereas 36% can be explained by firm specific characteristics. The rest of the explained variation is explained by the industry and year fixed effects. These partial correlations show that firm specific characteristics are more important in explaining the overall amount of variation in labor market power than are labor market characteristics, but there is still much of the variation left unexplained.

The second two models introduce labor market fixed effects and then firm fixed effects. While these controls can capture unobservable characteristics of the labor market and firm that may influence labor market power, the fixed effects change the interpretation of the results and pose a difficult task for the individual controls to influence the market power of a firm labor market over time. Hence the primary interest in these results is the correlation that can be explained by the various sets of controls. However, it is possible to look at the firm specific controls in the second model when just the labor market fixed effects are included, as they attempt to explain the variation within a labor market across firms.

The second model, with results beginning in column (3), adds labor market fixed effects to the regression. These fixed effects capture market specific characteristics that stay constant

over time, such as market specific moving costs. Examining the firm specific characteristics shows that most are the same sign as the results in column (1), with larger, foreign-owned, and growing firms having more market power, but firms low concentrated labor markets having less.

Adding labor market fixed effects to the model increases the overall amount of variation explained to 0.365. Now the majority of the variation is explained by the labor market fixed effects. While the firm specific observables explain more variation in market power than the observable labor market characteristics, the unobserved labor market characteristics are more important.

The last model adds firm fixed effects and the results are displayed in column (5). The foreign ownership and firm age controls are dropped as they do not vary over time in combination with the year effects. The interpretation of the coefficients changes some as now they explain how labor market power changes over time within a firm. With the inclusion of the firm fixed effects, the amount of variation in market power that can be explained has increased significantly. Mechanically, all of the new variation is explained by the firm fixed effects, as they are the only new controls added to the model. While this adds a lot of new variables, the adjusted  $R^2$  still reports a significant increase in variation explained. The observable characteristics of the firm explain more variation in market power than both the observed and unobserved labor market characteristics. This makes sense as there is probably not much variation in labor market characteristics over time.

Overall, the results in Table 6 show that there is more within labor market variation in labor market power than there is between labor market variation. The results confirm the traditional theories of monopsony, that the labor market influences the market power of the firms in the market. However, the results also support the new theories of monopsony, that there is variation in market power across firms within the same labor market. The results provide the first attempt at trying to quantify the importance of each set of characteristics, which enables the determination that firm characteristics are more important in explaining

the overall variation in labor market power.

## 8 Extensions and Robustness Checks

In this section, I will first consider an extension of this research, and then provide some robustness checks. As previously mentioned, the extension considers how market power enhances our understanding of firm behavior, and how this might inform policy analysis. I will specifically analyze whether firms with market power respond differently to an increase in labor costs than a firm operating in a competitive labor market.

To do this, I first develop predictions for how firms' market power would respond to an increase in labor costs, and how firms with more market power would respond differently than competitive firms. I test these predictions using a natural experiment surrounding the passage of a set of Labor Laws in 2003. This is following work I have done that uses the same natural experiment to identify how the law change impacted standard firm outcomes (2012). Labor Law 13 significantly increased the size of severance payments firms were required to pay, decentralized the setting of minimum wages, and increased the restrictions on the use of temporary workers. Using difference-in-difference methods, my other work found that the labor laws increased the total costs of labor, decreased output and employment, and increased the capital-labor ratio of treated firms. The natural experiment used in the analysis is based on differing levels of enforcement of the laws across different firms<sup>15</sup>. The paper uses two complementary approaches for determining which firms are more likely to comply with the law and which are not. The first approach argues that large firms are more likely to comply with the new laws, whereas the small, domestically-owned firms are less likely to do so. The second approach states that firms located in districts where the provincial capital is located are more likely to comply with the law, whereas firms located in other districts are less likely to comply. This second approach also enables the use of a matched difference-in-differences

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<sup>15</sup>The idea of different compliance levels is supported theoretically by Basu, Chau, and Kanbur (2010) among others, and empirically by Harrison and Scorse (2004, 2010), and Manning and Rosead (2007).

estimator, which constructs the control group by selecting the firms not in the district with the provincial capital that are most similar to the treated firms.

The same natural experiment can be used here to test my measure of market power. Let  $\beta > 0$  be the slope of the labor demand curve and  $\alpha < 0$  be the slope of the labor supply curve. If the change in the labor laws increases the costs of labor by  $\delta$ , then the change in wages for firms with market power would be  $\delta(1 - \frac{\alpha}{2\alpha - \beta})$ . If the firm sources labor from a competitive labor market, then  $\alpha = 0$  and the change in wages would be equal to  $\delta$ . Since  $\alpha > 0$  and  $\beta < 0$ , the monopsonistic firms have a smaller change in wages than do competitive firms. The change in labor demand for firms with market power would be  $\frac{\delta}{\beta - 2\alpha}$  which is smaller than the similar change for competitive firms,  $\delta/\beta$ . It is straightforward to show that market power should decrease in response to the increased labor costs<sup>16</sup>

The estimates below use standard cutoffs for firm size, with large firms having more than 250 employees, and small firms having less than 50. Firms were assigned to their respective treatment and control groups based on their average size between 2000 and 2002 so the composition of the treatment and control groups stays fixed across the study period. This removes any bias associated with firms changing groups based their responses to the policy change. The data from 2003 is excluded from the comparison as that was an adjustment year. Note that the sample size is smaller as the years are restricted to 2000-2002 and 2004-2006 for this analysis, and firms having between 100 and 250 employees are also excluded.

Table 7 reports the results of the increased labor costs on the distribution of market power. The prediction is that market power should decrease. The first two columns report the results using firm size to identify the treatment and control groups. Columns 3 and 4 use the location of the firm to identify the treatment and control groups, and the last columns build on this by using propensity score matching to construct the control group. The odd numbered columns only include the treatment dummies, and year, industry and

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<sup>16</sup>Let  $p_0$  be the Y-intercept of the labor demand curve and  $y_0$  be the Y-intercept of the labor supply curve, then the change in the labor law shifts the labor supply curve up by  $\delta$ , which changes the Y-intercept to  $y_0 + \delta$ . So, the resulting change in  $E$  can be calculated as  $\frac{\partial E}{\partial y_0} = \frac{\alpha p_0 \beta - 2\alpha^2 p_0}{(y_0(\alpha - \beta) + \alpha p_0)^2} < 0$ .



region dummies. The even numbered columns also include firm specific controls for capital, firm age, foreign ownership, the mandated minimum wage, product market concentration, and labor market concentration.

The coefficient of interest is on the interaction term between *Treated* and *Post* – 2003. Whenever the coefficient is statistically significant, it is negative, which supports the predicted impact of the policy change. This result suggests that as labor costs increased due to the increased firing restrictions mandated by the new labor law, the amount of market power firms had decreased. The law change shifted the labor supply curve inward, and if the labor demand curve did not change, the distance between the marginal revenue product of labor and the wage was reduced.

I next consider how the law change differentially impacted the wages of firms with market power and those without. To facilitate this, I create a dummy variable that is equal to 1 if firms have an average level of market power greater than 2, and equal to 0 if the market power is below 0.33. These cutoffs are the same as those used Table 4. This new dummy variable is interacted with the treatment and post-2003 dummy variables to create a triple interaction. The prediction is that firms with market power will have a smaller reaction to the law change than firms that operate competitively. Table 8 reports the results and the coefficient on the triple interaction is negative and significant in the last three columns. The coefficient on the triple interaction in the last column says that firms with market power had a 6.6% smaller response in wages to the law change than did firms without market power. Competitive firms would see their labor costs increase by the full amount of the value of the increased firing restrictions, whereas firms with market power are able to defray some of those costs.

The results of a similar exercise, but now examining the employment response, are reported in Table 9. The coefficient on the triple interaction is only significant in one specification, and it is positive. This is not the predicted relationship, though the result appears to be sensitive to the specification as it only appears once.

I next consider the robustness of my results to various decisions that I made in calculating my main results. I first test the impact of the data cleaning procedures on my results. The results using the raw data are presented in the first panel of Table 10. The estimate using the raw data has a higher mean, but a lower median. This can be attributed to the raw data being noisier. This is reflected in the distribution of firms as well, with the raw data have a larger percentage of firms without market power, and not as many firms in the middle category. There are fewer observations for the raw data since I impute missing values in the main analysis.

In the main analysis, I estimated the production function separately by four-digit industry, of which there were 83 industries. For comparison purposes, I also present the results estimating the production function separately by two-digit industry, of which there are 19. These estimates using the two-digit should be less precise, as they assume more firms of different types share the same production technology. The estimates using these larger groupings are presented in the second panel of Table 10. The median value of market power is lower using the broader groupings, and the categories show that a lower percentage of firms have at least some market power. However, fewer industries pass all of the specification tests, so the results are less representative.

The third panel of Table 10 report the results when only looking at the firms in industries where all of the parameters of the production function were estimated to be positive. These extra constraints are applied in addition to all of the specification tests included in the main analysis. With the additional constraints, the sample size is cut almost in half, though the median value of market power only increased to 2.10. The composition of the different categories of market power are also very similar to the main results.

The next robustness check I perform considers an alternative method for estimating the production function. As mentioned above, another standard approach for estimating production functions is developed by Akerberg, Caves, and Frazer (ACF 2006). In order to apply this approach to this analysis, I need an instrument to break the endogenous choice

of labor with the firms' market power. I use the labor market HHI calculated at the local geographic district as an instrument for labor in the production function. The density of the local labor market influences the firms' choice of labor, but is independent of the firms' output levels, except through its impact on the amount of labor a firm hires. I use the predicted amount of labor hired in the two-step procedure outlined by Akerberg, Caves, and Frazer. To obtain standard errors for the estimates, I bootstrap the entire procedure 200 times (including the instrument estimation), blocking the sample selection at the firm level, and estimating a separate production function for each four-digit industry as done in the main analysis.

The estimates of market power using the ACF procedure are reported in the third panel of Table 10. The results show significantly more market power than the main results, with over 80% of firms having some amount of market power, and almost 50% having a lot of market power. Since the wages for the firms are the same in both approaches, the ACF procedure has estimated much higher marginal revenue products for each firm. Accordingly, the main results using the Blundell-Bond procedure are a more conservative estimate of the market power of firms.

The last robustness check I perform is to leverage the panel nature of my data and estimate the production function separately by individual firms. I have 19 years of data, though, only each firm has only 12.4 years of data on average. So, I am not able to do this for every firm, but I can get results for firms where I do have enough observations. The results using this method are reported in the last two lines of Table 10. The results show significantly more market power for most firms, as evidenced by the median level of market power being 15 and over 82% of the firms having a lot of market power.

All of these robustness checks show estimates for the market power of firms either similar to or greater than the main results presented in Table 4. This suggests that the main results are a conservative estimate for the degree of monopsony in the labor markets of Indonesia.

## 9 Conclusion

This paper has measured monopsonistic behavior by estimating the marginal revenue product for each firm and comparing that to the average wage the firm pays its workers. This was done for both production and non-production workers using Blundell and Bond's System-GMM technique for estimating production functions. I find that over half the firms in the sample have a significant amount of market power, with a median value of Pigou's  $E$  of 1.93. To my knowledge, this is the first direct evidence for monopsonistic behavior by firms in an emerging economy.

My approach fits the data reasonably well, as over 84% of the observations are in industries that pass all of the specification tests. I also find that firms with a greater share of the labor market have more market power, and firms have less market power in more competitive districts. I also use the labor law change in 2003 as a natural experiment to show that the measure of market power responds to the increased labor costs as theory would predict.

I then considered whether a firm's market power is more attributable to firm level characteristics or labor market factors. My results show that while labor market characteristics are important in explaining the variation in market power, the firm specific characteristics are more important.

This work sheds light on the policy discussion in emerging economies, as formal sector employment is often viewed as a key tool in reducing poverty for a large number of people. While formal sector employment may indeed be pulling a lot of people out of poverty, this research suggests that it could be playing an even larger role in reducing poverty if firms operated more competitively in the labor market.

Also, a common policy prescription is a minimum wage. With the traditional labor supply graph in mind, a minimum wage would move the firms' choice of labor along their existing labor supply curve. This policy is efficiency increasing if firms are facing an upward sloping labor supply curve<sup>17</sup>. However, the impact of the policy would be muted if firms are

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<sup>17</sup>Recent literature for developing countries has shown that minimum wage policies can increase wages,

facing different labor supply curves. The government could not implement a firm-specific minimum wage policy even if it knew what the optimal level should be. This paper shows that firms have different levels of market power, indicating that they are facing different labor supply curves, which would mitigate the impact of any minimum wage policy.

Moreover, this research suggests an additional avenue of policy prescriptions. Since, each firm's market power is due to them facing an upward sloping labor supply curve, any policy that flattens the labor supply curve would be making the labor market more efficient. This could be done by policies that make it easier for a firm to find additional workers, or by policies that reduce the variation in worker's preferences for firms. A policy of the first sort might be a job training program or an improved educational system that produces more qualified workers. A policy of the latter kind might be a firing restrictions regulation, that would reduce the perceived differences across firms in job security. Indeed, this is what I found in Table 7. In response to an increase in firing restrictions that were a part of Indonesia's Labor Law 13 passed in 2003, monopsonistic behavior decreased. Future research could investigate the impact of a national pension system on market power. Environments where a national pension is provided by the government should have lower variation in the total benefits provided to workers across firms. The lower variation would imply a flatter labor supply curve, and therefore a more competitive labor market.

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though that comes with negative employment effects (Gindling and Terrell 2005, 2010, Alatas and Cameron 2009).

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Table 1: Summary Statistics of All Indonesian Manufacturing Establishments

	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)
% Foreign Ownership	4.32	(18.20)	0.00	100.00
Output (bn-Rph)	19.58	(160.07)	0.00	17,769
Raw Materials (bn-Rph)	12.65	(90.36)	0.00	17,693
Investment (bn-Rph)	1.72	(92.75)	0.00	24,030
Capital Stock (bn-Rph)	18.49	(584.34)	0.00	179,044
% Output Exported	11.45	(29.28)	0.00	1,220
Value Added/Emp (mn-Rph)	22.71	(130.67)	-6.84	31,486
Firm Age	14.50	(14.49)	0.00	105.00
# Employees	192.03	(653.02)	10.00	42,649
% Production Wkrs	83.84	(14.23)	1.19	100.00
% w/ HS diploma	27.38	(26.86)	0.00	192.00
% w/ College degree	1.12	(2.71)	0.00	53.33
Avg Wage-PR (th-Rph)	4,261	(2,990)	0.78	137,339
Avg Wage-NP (th-Rph)	9,491	(79,403)	0.00	34,927,880
Labor Mkt Share	0.016	(0.066)	0.000	1.000
Labor Conc. 8CR	0.253	(0.127)	0.091	1.000
Num	306,217			

Notes: All values are in constant 2000 Rupiah (Rph). Data covers years 1988 - 2006. Standard deviations are in parentheses. The export data is only available for years 1990-2000, 2004, and 2006. The education information is available for years 1995-1997, and 2006. PR stands for Production workers and NP stands for Non-Production workers.

Table 2: Selected Cobb-Douglas Production Function Estimates by Industry using System-GMM

Industry	CRS						Num	Num	Hansen	AR(1)	AR(2)
	$\beta_{PR}$	$\beta_{NP}$	$\beta_k$	$\beta_m$	Sum	t-test	Firms	Instr.			
Meat Processing	0.18	-0.12	-0.01	0.93	0.99	0.042	48	33	0.16	0.00	0.31
Fish Processing	0.14	0.03	-0.02	0.80	0.96	0.215	718	33	0.82	0.12	0.28
Fruits and Veg.	0.16	-0.03	-0.05	0.72	0.80	1.052	103	33	0.74	0.00	0.71
Cooking Oils	0.03	0.02	-0.01	0.92	0.95	0.183	345	33	0.24	0.00	0.25
Dairy Products	0.09	-0.07	0.10	0.79	0.91	0.437	44	33	0.24	0.01	0.40
Grain Products	0.06	0.03	0.01	0.80	0.90	0.562	641	33	0.06	0.00	0.08
Starches	-0.01	0.02	-0.03	0.95	0.92	0.396	306	33	0.83	0.00	0.30
Animal Feeds	0.06	0.05	0.02	0.88	1.00	0.023	104	33	0.25	0.00	0.97
Bakery Products	0.16	0.04	0.02	0.83	1.05	0.315	844	33	0.70	0.00	0.36
Sugar	0.75	0.12	0.07	0.50	1.45	1.892	140	33	0.92	0.00	0.14
Apparel	0.47	0.02	0.04	0.50	1.03	0.226	2,943	33	0.36	0.00	0.50
Leather Prep.	0.16	0.12	-0.06	0.79	1.01	0.044	96	33	0.58	0.03	0.20
Leather Finishing	0.45	0.03	-0.03	0.68	1.13	0.496	175	33	0.87	0.00	0.38
Footwear	0.18	0.20	-0.02	0.64	1.01	0.033	548	33	0.97	0.00	0.99
Sawmilling	0.12	0.07	0.03	0.69	0.91	0.496	1,346	33	0.12	0.00	0.30
Plywood	0.30	-0.01	0.01	0.76	1.06	0.312	243	33	0.14	0.02	0.68
Builders' Carpentry	0.19	0.04	-0.01	0.75	0.97	0.149	539	33	0.72	0.07	0.53
Wood Containers	-0.12	0.10	0.03	0.71	0.71	1.111	72	33	0.20	0.16	0.75
Other Wood	0.17	0.00	0.10	0.67	0.94	0.227	572	33	0.55	0.00	0.94
Pulp and Paper	0.73	-0.03	0.11	0.49	1.29	1.427	171	33	0.08	0.00	0.26
Corrugated Paper	0.17	0.10	0.00	0.65	0.92	0.343	220	33	0.69	0.00	0.74
Other Paper	-0.25	0.25	-0.05	0.97	0.93	0.268	66	33	0.54	0.26	0.52
Book Publishing	0.24	0.16	-0.00	0.76	1.15	0.911	196	33	0.06	0.02	0.35
Newspapers	0.48	-0.08	0.15	0.58	1.14	0.457	41	33	0.75	0.00	0.68
Other Publishing	0.42	0.00	0.01	0.78	1.21	0.985	351	33	1.00	0.01	0.79
Printing	-0.02	0.20	0.06	0.72	0.96	0.183	99	33	0.32	0.00	0.23
Motor Vehicles	0.11	0.09	0.05	0.71	0.96	0.138	87	33	0.74	0.00	0.79
Vehicle Parts	0.12	-0.03	-0.01	0.84	0.92	0.297	208	33	0.30	0.01	0.15
Motorcycles	0.15	-0.08	-0.01	0.93	1.00	0.022	102	33	0.97	0.00	0.12
Bicycles	-0.10	-0.12	0.06	0.89	0.74	1.054	99	33	0.66	0.00	0.71
Raw Average	0.23	0.05	0.01	0.73	1.03	0.374	346	33	0.56	0.01	0.50

Notes: 30 of the 83 industry categories are presented here. P-Values are listed for specification tests.

Table 3: Comparing the Means of the Firms in Industries that Passed All Specification Tests to Firms that Did Not Pass

	Passed Spec. Tests		Did Not Pass		t-test
	Mean (1)	SD (2)	Mean (3)	SD (4)	
% Foreign Ownership	4.53	(18.71)	3.52	(16.14)	13.72
Output (bn-Rph)	20.99	(173.41)	14.36	(95.52)	12.87
Raw Materials (bn-Rph)	13.40	(95.32)	9.88	(68.89)	10.58
Investment (bn-Rph)	1.68	(82.72)	1.89	(122.93)	0.42
Capital Stock (bn-Rph)	19.45	(642.36)	14.91	(279.13)	2.66
% Output Exported	12.06	(29.87)	9.22	(26.90)	20.98
Value Added/Emp (mn-Rph)	22.78	(134.23)	22.47	(116.56)	0.58
Firm Age	14.41	(14.63)	14.85	(13.93)	6.87
# Employees	208.26	(709.49)	131.92	(370.10)	37.29
% Production Wkrs	84.06	(13.88)	83.02	(15.40)	15.32
% w/ HS diploma	28.10	(26.63)	24.75	(27.54)	12.92
% w/ College degree	1.09	(2.62)	1.22	(3.00)	4.70
Avg Wage-PR (th-Rph)	4,339	(2,936)	3,972	(3,169)	26.62
Avg Wage-NP (th-Rph)	9,667	(88,169)	8,813	(25,358)	4.08
Labor Market Share	0.016	(0.067)	0.014	(0.059)	8.42
Labor Conc. 8CR	0.251	(0.127)	0.259	(0.126)	13.70
Num Firm-Year Obs.	241,093	.	65,124	.	.
Num. Industries	61	.	22	.	.

Notes: All values are in constant 2000 Rupiah (Rph). Data covers years 1988 - 2006. Standard deviations are in parentheses. The export data is only available for years 1990-2000, 2004, and 2006. The education information is available for years 1995-1997, and 2006. PR stands for Production workers and NP stands for Non-Production workers.

Table 4: Summary of Pigou's Measure of Market Power,  $E$

	Num (1)	Mean (2)	Median (3)	Percent of firms with		
				$E < 0.33$ (4)	$0.33 \leq E \leq 2$ (5)	$E > 2$ (6)
Production Workers	241,093	5.35 (0.30)	1.93	40.35	28.44	31.21
Non-Production Workers	177,473	10.17 (3.58)	0.40	44.43	22.47	33.11

Notes: Data covers years 1988 - 2006. Means are weighted by the number of employees of each type in each firm. Standard errors are in parentheses.

Table 5: Checking the Relationship Between Traditional Measures of Market Power and Pigou's E

	Dependent Var. = $\ln(\text{Pigou's } E+1)$			
	(1)	(2)	(3)	(4)
Firm Market Share	0.742*** (0.128)	0.768*** (0.154)		
Labor Market Concentration - Low			-0.093*** (0.024)	-0.112*** (0.027)
Labor Market Concentration - High			0.007 (0.026)	0.026 (0.028)
Local Unemployment		0.023*** (0.004)		0.021*** (0.004)
Firm Age		-0.001 (0.001)		0.002** (0.001)
Foreign Ownership		0.280*** (0.026)		0.324*** (0.025)
Product Market Concentration - Low		0.054 (0.040)		0.050 (0.043)
Product Market Concentration - High		0.137*** (0.045)		0.251*** (0.052)
Constant		0.135 (0.104)		0.203* (0.107)
Adj. $R^2$	0.141	0.150	0.133	0.147
Num	290,801	227,777	240,542	188,035

Notes: Data covers years 1990 - 2006. Standard errors are in parentheses. All models include year, industry, and region dummies, and are weighted by the number of production employees in each firm. Labor market concentration is measured by the concentration ratio of the 8 largest firms in the local labor market. High (low) values are defined as the highest (lowest) quartile. Product market concentration is measured by the HHI, and high values for the index are greater than or equal to 0.25. Low HHI are values less than or equal to 0.15.

Table 6: GLS Regressions With Pigou's  $E$  for Production Workers as the Dependent Variable

	Dependent Var. = $\ln(\text{Pigou's } E+1)$					
	Coef. (1)	Partial Corr. (2)	Coef. (3)	Partial Corr. (4)	Coef. (5)	Partial Corr. (6)
Labor Mkt 8CR - Low	-0.104* (0.060)	0.003	-0.060** (0.026)	0.000	-0.024 (0.022)	0.003
Labor Mkt 8CR - High	-0.016 (0.045)		-0.011 (0.037)		0.029 (0.028)	
Local Unemployment	0.011 (0.008)		-0.002 (0.004)		-0.003 (0.003)	
Foreign Owned	0.096** (0.041)		0.089*** (0.030)			
Firm Age	0.000 (0.004)		-0.001 (0.001)			
Output Growth/100	0.027*** (0.006)	0.098	0.029*** (0.007)	0.078	0.100*** (0.030)	0.020
Product Mkt HHI - Low	-0.047 (0.081)		-0.104** (0.044)		-0.033 (0.024)	
Product Mkt HHI - High	-0.010 (0.057)		0.007 (0.043)		0.033 (0.029)	
$\ln(\text{Capital})$	0.140*** (0.017)		0.131*** (0.005)		0.060*** (0.011)	
Constant	-1.553*** (0.335)		-1.371*** (0.094)		-0.303 (0.203)	
L-Mkt Fixed Effects	No		Yes	0.123	Yes	0.013
Firm Fixed Effects	No		No		Yes	0.529
Adj. $R^2$	0.276		0.365		0.701	
Num	126,858		126,858		126,858	

Notes: Data covers years 1990 - 2006 for firms with estimates of the production function that met all of the specification tests. The labor market is defined as the local district. Standard errors are in parentheses. Industry and year dummies are included in all regressions. All models are weighted by the number of production employees at each firm. In models without firm effects, standard errors are clustered at the district level. The even numbered columns contain partial correlation coefficients. They do not sum up to the total R-squared because of the industry and year dummies.

Table 7: Difference-in-Differences Results for Impact of Labor Law on Market Power

Dependent Var = ln (Pigou's E +1)	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.577*** (0.017)	0.202*** (0.023)	0.101*** (0.015)	0.083*** (0.017)	0.022* (0.011)	0.021* (0.013)
Post-2003	0.148*** (0.018)	0.129*** (0.036)	0.132*** (0.015)	-0.006 (0.032)	0.119*** (0.017)	0.129*** (0.023)
Treated * Post-2003	-0.058** (0.023)	-0.018 (0.025)	-0.038* (0.019)	-0.038* (0.021)	0.005 (0.017)	0.001 (0.018)
Constant	1.796*** (0.162)	0.788 (0.905)	1.962*** (0.124)	0.724 (0.714)	1.118*** (0.126)	1.572** (0.719)
Controls	No	Yes	No	Yes	No	Yes
Adj. $R^2$	0.157	0.191	0.089	0.163	0.088	0.163
Num	40,384	31,247	66,572	52,477	66,572	52,477

Notes: Data covers years 2000-2002, and 2004-2006. Standard errors are in parentheses. All models include year, region, and industry effects. Controls include capital, minimum wage, firm age, foreign ownership, product market concentration, and labor market concentration.

Table 8: Difference-in-Differences Results for Impact of Labor Law on Wages of Production Workers

Dependent Var = ln (Prod. Wages)	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.315*** (0.015)	-0.296*** (0.017)	0.134*** (0.011)	0.117*** (0.010)	0.127*** (0.015)	0.114*** (0.013)
Post-2003	-0.001 (0.013)	0.042 (0.026)	0.151*** (0.011)	0.068*** (0.021)	0.177*** (0.021)	-0.037 (0.025)
Treated * Post-2003	-0.030 (0.024)	-0.042* (0.022)	0.114*** (0.016)	0.112*** (0.014)	0.104*** (0.022)	0.107*** (0.020)
Mkt Power	-0.005 (0.012)	-0.277*** (0.011)	0.132*** (0.008)	-0.217*** (0.008)	0.147*** (0.016)	-0.152*** (0.015)
Mkt Power * Treated	0.112*** (0.020)	0.001 (0.019)	-0.037** (0.015)	-0.035*** (0.014)	-0.043** (0.020)	-0.038** (0.018)
Mkt Power * Post-2003	0.062*** (0.016)	0.212*** (0.014)	0.049*** (0.012)	0.193*** (0.010)	0.121*** (0.026)	0.179*** (0.023)
Mkt-Pow*Treat*Post-03	0.043 (0.030)	-0.006 (0.028)	-0.024 (0.022)	-0.062*** (0.020)	-0.097*** (0.032)	-0.066** (0.028)
Constant	9.081*** (0.118)	5.606*** (0.455)	8.510*** (0.089)	6.602*** (0.372)	8.515*** (0.125)	7.342*** (0.562)
Controls	No	Yes	No	Yes	No	Yes
Adj. $R^2$	0.286	0.428	0.231	0.409	0.246	0.396
Num	29,167	28,963	47,163	46,810	17,533	17,501

Notes: Data covers years 2000-2002, and 2004-2006. Standard errors are in parentheses. All models include year, region and industry effects. Controls include output, capital and minimum wage. Firms with market power are those with Pigou's  $E > 2$ , and they are compared to firms with  $E < 0.33$ .



Table 9: Difference-in-Differences Results for Impact of Labor Law on the Number of Production Workers

Dependent Var = ln (Prod. Jobs)	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	2.625*** (0.027)	1.622*** (0.025)	-0.050** (0.024)	-0.109*** (0.014)	-0.020 (0.031)	-0.074*** (0.019)
Post-2003	0.022* (0.013)	-0.048 (0.030)	0.030 (0.021)	-0.237*** (0.029)	0.054 (0.042)	-0.210*** (0.036)
Treated * Post-2003	-0.149*** (0.044)	-0.170*** (0.034)	-0.049 (0.033)	-0.063*** (0.021)	-0.048 (0.045)	-0.042 (0.029)
Mkt Power	-0.051*** (0.008)	-0.492*** (0.011)	0.551*** (0.017)	-0.656*** (0.011)	0.562*** (0.035)	-0.730*** (0.022)
Mkt Power * Treated	0.216*** (0.032)	0.032 (0.026)	0.064* (0.035)	0.080*** (0.020)	0.020 (0.046)	0.048* (0.027)
Mkt Power * Post-03	0.047*** (0.011)	0.294*** (0.013)	-0.197*** (0.024)	0.289*** (0.015)	0.045 (0.055)	0.292*** (0.033)
Mkt-Pow*Treat*Post-2003	0.072 (0.052)	-0.017 (0.040)	0.114** (0.052)	-0.016 (0.030)	-0.116 (0.072)	0.019 (0.042)
Constant	2.883*** (0.091)	-0.283 (0.532)	2.741*** (0.133)	-3.991*** (0.523)	2.475*** (0.110)	-5.267*** (0.783)
Controls	No	Yes	No	Yes	No	Yes
Adj. $R^2$	0.797	0.864	0.157	0.700	0.141	0.719
Num	29,167	28,963	47,163	46,810	17,533	17,501

Notes: Data covers years 2000-2002, and 2004-2006. Standard errors are in parentheses. All models include year, region and industry effects. Controls include output, capital and minimum wage. Firms with market power are those with Pigou's  $E > 2$ , and they are compared to firms with  $E < 0.33$ .

Table 10: Robustness Checks for Pigou's  $E$  for Production Workers

	Num (1)	Mean (2)	Median (3)	Percent of firms with		
				$E < 0.33$ (4)	$0.33 \leq E \leq 2$ (5)	$E > 2$ (6)
Raw Data	245,778	13.34 (1.62)	1.37	46.80	22.48	30.72
Two-Digit Industries	184,808	5.27 (0.40)	1.34	45.41	27.02	27.58
All Positive Betas	132,417	5.58 (0.56)	2.10	39.30	30.13	30.57
Akerberg-Caves-Frazer	200,505	10.19 (0.34)	2.76	18.56	32.57	48.87
Firm Specific Prod. Fcn.	122,138	84.86 (5.21)	15.01	7.95	9.96	82.09

Notes: Data covers years 1988 - 2006. Means are weighted by the number of employees in each firm. Standard errors are in parentheses.