ESSAYS ON THE BEHAVIOR OF FIRMS IN THE INDONESIAN LABOR MARKET

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Peter William Brummund

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Peter William Brummund, Ph.D.
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The greatest productive asset for most people in the world is their own labor. Many poor people employ their labor in subsistence agriculture or in informal jobs. A direct route to lift these people out of poverty is to move them into formal sector jobs which provide higher wages and more benefits. It is also important for poverty alleviation to improve the wages and benefits provided to people already working in formal sector jobs. The more people that can be employed in formal sectors jobs with higher wages, the fewer people there will be living in poverty. My research deals with issues in this arena.

The first chapter investigates whether firms behave monopsonistically, which would result in lower wages and lower employment than a competitive outcome would. The results show that about 60% of the manufacturing firms do behave monopsonistically in the labor market. The second chapter analyzes the impact of increased firing restrictions on the behavior of firms, and finds that labor costs increase, output decreases, and the capital-labor ratio increases. The third chapter looks how big of an impact the monopsonistic behavior of firms has on the poverty rate in Indonesia, and finds that poverty would be 8.5% to 23% lower if firms behaved competitively in the labor market.

BIOGRAPHICAL SKETCH

I was born in Watertown, Wisconsin to parents who emphasized the importance of education and encouraged me to do my best. While advancing through the outstanding local public school system, I developed a love for problem solving, especially logic and math puzzles. I continued my education at Taylor University, a liberal-arts school in Upland, Indiana where I focused my problem solving interests on a degree in computer science.

While working as a Systems Analyst for Eli Lilly and Company, I became involved in the issues of poverty and justice in the cities in the United States. Because of my experience in the urban community of Indianapolis, I chose to study the economic systems that influenced these situations. I began by taking courses in economics at night and continued with a Masters degree in Development Studies at the London School of Economics and Political Science. Then I came to Cornell University, where I will complete my formal education with a PhD in Economics.

I am grateful for the training that I have received at each step along the way, and I look forward to continuing to investigate the issues related to poverty in the years ahead.

I dedicate this dissertation to my amazing wife, Karen. She has encouraged and supported me along every step of this process. Convincing her to marry me is my greatest accomplishment.

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CHAPTER 1

VARIATION IN MONOPSONISTIC BEHAVIOR ACROSS ESTABLISHMENTS: EVIDENCE FROM THE INDONESIAN LABOR MARKET

1.1 Introduction

How much market power do individual firms[1] 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

[1]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.

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[2] is the difference between a worker's marginal revenue product and the wage he or she is paid, normalized by the wage (Pigou 1924)[3]. 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 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[4].

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,

[2]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).

[3]This measure is similar to the Lerner Index used to measure product market power.

[4]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.

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; Ackerberg, Caves, and Frazer 2006)[5]. 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.

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.

[5]Van Biesebroeck (2007) provides a useful summary of the various techniques.

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[6]. 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

[6] Author's calculations based on World Bank's World Development Indicators.

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 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 than 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.

1.2 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[7]. 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.

The agricultural economics literature has also estimated the MRPL of work-

[7]The top end of that range is for the Transportation Equipment industry, and is the only estimate above 100%.

ers, 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 competitive 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.

1.3 Empirical Approach

1.3.1 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. 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:

$$E = \frac{R'(L) - W(L)}{W(L)}. \tag{1.1}$$

It is easy to show that $E = \epsilon^{-1}$, where ϵ is the elasticity of the labor supply curve[8]. 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, 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[9]. β_j is the factor share of factor $j \in \{L, K\}$. The most direct way to estimate this is to convert it

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

[9]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.

to logs and estimate the equation:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \epsilon_{it}, \tag{1.2}$$

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:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \omega_{it} + \nu_{it}, \tag{1.3}$$

with ω_{it} representing firm-specific productivity and ν_{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, Ackerberg, 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.

Ackerberg, 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 Ackerberg, 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

$$y_{it} = \rho y_{it-1} + \beta_L(l_{it} - \rho l_{it-1}) + \beta_K(k_{it} - \rho k_{it-1}) + (\gamma_t - \rho\gamma_{t-1}) + (\delta_i(1-\rho)\eta_{it} + \nu_{it} + \rho\nu_{it-1}) \quad (1.4)$$

where γ_t is a year fixed effect, δ_i is a firm fixed effect, and ρ 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:

$$min_{\theta \in \Theta} \{\hat{\pi} - h(\theta)\}' \hat{\Xi}^{-1} \{\hat{\pi} - h(\theta)\}, \tag{1.5}$$

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:

$$\begin{aligned} AsyVar(\hat{\theta}) &= \frac{1}{n}[\hat{H}'\Xi^{-1}\hat{H}]^{-1} & (1.6) \\ &= (\hat{H}'[avar(\hat{\pi})]^{-1}\hat{H})^{-1}. & (1.7) \end{aligned}$$

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 β_L. To weaken the impact of this assumption, I estimate the production function separately by four-digit industries[10]. I also check the validity of this assumption by estimating the more

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

flexible transcendental-logarithmic function. The trans-log production function takes the form,

$$y_{it} = \beta_0 + \sum_{N} \beta_N ln(N_{it}) + (1/2) \sum_{N} \sum_{Q} \beta_{NQ} ln(N_{it}) ln(Q_{it}), \tag{1.8}$$

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

$$MRPL_{it} = \frac{\partial Y_{it}}{\partial L_{it}} = \frac{\hat{\beta}_{L_j} Y_{it}}{L_{it}}, \tag{1.9}$$

for firm i, year t, and industry j. It is then straightforward to calculate the firm-year specific measure of market power from equation (3.1).

1.3.2 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.

1.3.3 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, than 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[11]. 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.

1.4 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 follow-

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

ing 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 1.1. 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.

1.5 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,

$$y_{it} = \beta_{L_{PR}} l_{it}^{PR} + \rho\beta_{L_{PR}} l_{it-1}^{PR} + \beta_{L_{NP}} l_{it}^{NP} + \rho\beta_{L_{NP}} l_{it-1}^{NP} + \beta_K k_{it} + \rho\beta_K k_{it-1} + \beta_M m_{it} + \rho\beta_M m_{it-1} + \rho y_{it-1} + \delta_i + \mu_{it}, \tag{1.10}$$

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 1.2 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 1.2. 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 1.3 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 1.3 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 of 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 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

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

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,

$$\frac{\partial Y}{\partial L_{PR}} = \frac{\hat{\beta}_{L_{PR}}Y}{L_{PR}} \tag{1.11}$$

$$\frac{\partial Y}{\partial L_{NP}} = \frac{\hat{\beta}_{L_{NP}}Y}{L_{NP}} \tag{1.12}$$

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 1.4 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 1.4 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.

1.6 Testing the Measure of Market Power

Table 1.5 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[12].

The first column in Table 1.5 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

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

predict, 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.

1.7 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[13]. 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

$$e_{ijt} = \alpha_0 + \mathbf{X_{it}}\alpha_\mathbf{1} + \mathbf{Y_{jt}}\alpha_\mathbf{2} + \gamma_j + \nu_i + \epsilon_{ijt}, \tag{1.13}$$

[13]I use feasible-GLS because its a more efficient estimator than OLS, giving more weight to observations with lower variance.

with $\mathbf{X_{it}}$ being a set of time-varying firm characteristics, $\mathbf{Y_{jt}}$ a set of time-varying labor market characteristics, γ_j a labor market fixed effect, and ν_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. 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[14]. 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.

[14]I drop 1988 and 1989 from this stage of the analysis.

Table 1.6 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 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 1.6 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.

1.8 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[15]. The paper uses two

[15] 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).

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 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 δ, 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 δ. 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, δ/β. It is straightforward to show that market power should decrease in response to the increased labor costs[16]

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

[16]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 δ, which changes the Y-intercept to $y_0 + \delta$. So, the resulting change in E can be calculated as $\frac{\partial E}{\partial y_0} = \frac{\alpha p_0 \beta - 2\alpha^2 p_0}{(y_0(\alpha-\beta)+\alpha p_0)^2} < 0$.

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 1.7 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 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 1.4. 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 1.8 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 1.9. 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 1.10. 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 1.10. 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 1.10 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 Ackerberg, 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 Ackerberg, 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 1.10. 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 1.10. 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 1.4. This suggests that the main results are a conservative estimate for the degree of monopsony in the labor markets of Indonesia.

1.9 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[17]. However, the impact of the policy would be muted if firms are 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

[17]Recent literature for developing countries has shown that minimum wage policies can increase wages, though that comes with negative employment effects (Gindling and Terrell 2005, 2010, Alatas and Cameron 2009).

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 1.7. 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.

Table 1.1: 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 1.2: Selected Cobb-Douglas Production Function Estimates by Industry using System-GMM

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

Notes: 30 of the 83 industry categories are presented here. P-Values are listed for specification tests. There are 33 instruments in every estimation.

Table 1.3: 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		
	Mean	SD	Mean	SD	t-test
	(1)	(2)	(3)	(4)	(5)
% 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 1.4: Summary of Pigou's Measure of Market Power, E

				Percent of firms with		
	Num	Mean	Median	$E < 0.33$	$0.33 \leq E \leq 2$	$E > 2$
	(1)	(2)	(3)	(4)	(5)	(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 1.5: Checking the Relationship Between Traditional Measures of Market Power and Pigou's E

	Dependent Var. = ln(Pigou's E+1)			
	(1)	(2)	(3)	(4)
Firm Market Share	0.742***	0.768***		
	(0.128)	(0.154)		
Labor Market Concentration - Low			-0.093***	-0.112***
			(0.024)	(0.027)
Labor Market Concentration - High			0.007	0.026
			(0.026)	(0.028)
Local Unemployment		0.023***		0.021***
		(0.004)		(0.004)
Firm Age		-0.001		0.002**
		(0.001)		(0.001)
Foreign Ownership		0.280***		0.324***
		(0.026)		(0.025)
Product Market Concentration - Low		0.054		0.050
		(0.040)		(0.043)
Product Market Concentration - High		0.137***		0.251***
		(0.045)		(0.052)
Constant		0.135		0.203*
		(0.104)		(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 1.6: GLS Regressions With Pigou's E for Production Workers as the Dependent Variable

	Dependent Var. = ln(Pigou's E+1)					
	Coef.	Partial Corr.	Coef.	Partial Corr.	Coef.	Partial Corr.
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Mkt 8CR - Low	-0.104*		-0.060**		-0.024	
	(0.060)		(0.026)		(0.022)	
Labor Mkt 8CR - High	-0.016	0.003	-0.011	0.000	0.029	0.003
	(0.045)		(0.037)		(0.028)	
Local Unemployment	0.011		-0.002		-0.003	
	(0.008)		(0.004)		(0.003)	
Foreign Owned	0.096**		0.089***			
	(0.041)		(0.030)			
Firm Age	0.000		-0.001			
	(0.004)		(0.001)			
Output Growth/100	0.027***		0.029***		0.100***	
	(0.006)		(0.007)		(0.030)	
Product Mkt HHI - Low	-0.047	0.098	-0.104**	0.078	-0.033	
	(0.081)		(0.044)		(0.024)	
Product Mkt HHI - High	-0.010		0.007		0.033	0.020
	(0.057)		(0.043)		(0.029)	
ln(Capital)	0.140***		0.131***		0.060***	
	(0.017)		(0.005)		(0.011)	
Constant	-1.553***		-1.371***		-0.303	
	(0.335)		(0.094)		(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 1.7: Difference-in-Differences Results for Impact of Labor Law on Market Power

Dependent Var = ln (Pigou's E +1)	By Firm Size (1)	(2)	By Location (3)	(4)	Matched Control (5)	(6)
Treated	0.577***	0.202***	0.101***	0.083***	0.022*	0.021*
	(0.017)	(0.023)	(0.015)	(0.017)	(0.011)	(0.013)
Post-2003	0.148***	0.129***	0.132***	-0.006	0.119***	0.129***
	(0.018)	(0.036)	(0.015)	(0.032)	(0.017)	(0.023)
Treated * Post-2003	-0.058**	-0.018	-0.038*	-0.038*	0.005	0.001
	(0.023)	(0.025)	(0.019)	(0.021)	(0.017)	(0.018)
Constant	1.796***	0.788	1.962***	0.724	1.118***	1.572**
	(0.162)	(0.905)	(0.124)	(0.714)	(0.126)	(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 1.8: Difference-in-Differences Results for Impact of Labor Law on Wages of Production Workers

Dependent Var = ln (Prod. Wages)	By Firm Size (1)	(2)	By Location (3)	(4)	Matched Control (5)	(6)
Treated	0.315***	-0.296***	0.134***	0.117***	0.127***	0.114***
	(0.015)	(0.017)	(0.011)	(0.010)	(0.015)	(0.013)
Post-2003	-0.001	0.042	0.151***	0.068***	0.177***	-0.037
	(0.013)	(0.026)	(0.011)	(0.021)	(0.021)	(0.025)
Treated * Post-2003	-0.030	-0.042*	0.114***	0.112***	0.104***	0.107***
	(0.024)	(0.022)	(0.016)	(0.014)	(0.022)	(0.020)
Mkt Power	-0.005	-0.277***	0.132***	-0.217***	0.147***	-0.152***
	(0.012)	(0.011)	(0.008)	(0.008)	(0.016)	(0.015)
Mkt Power * Treated	0.112***	0.001	-0.037**	-0.035***	-0.043**	-0.038**
	(0.020)	(0.019)	(0.015)	(0.014)	(0.020)	(0.018)
Mkt Power * Post-2003	0.062***	0.212***	0.049***	0.193***	0.121***	0.179***
	(0.016)	(0.014)	(0.012)	(0.010)	(0.026)	(0.023)
Mkt-Pow*Treat*Post-03	0.043	-0.006	-0.024	-0.062***	-0.097***	-0.066**
	(0.030)	(0.028)	(0.022)	(0.020)	(0.032)	(0.028)
Constant	9.081***	5.606***	8.510***	6.602***	8.515***	7.342***
	(0.118)	(0.455)	(0.089)	(0.372)	(0.125)	(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 1.9: Difference-in-Differences Results for Impact of Labor Law on the Number of Production Workers

Dependent Var =	By Firm Size		By Location		Matched Control	
ln (Prod. Jobs)	(1)	(2)	(3)	(4)	(5)	(6)
Treated	2.625***	1.622***	-0.050**	-0.109***	-0.020	-0.074***
	(0.027)	(0.025)	(0.024)	(0.014)	(0.031)	(0.019)
Post-2003	0.022*	-0.048	0.030	-0.237***	0.054	-0.210***
	(0.013)	(0.030)	(0.021)	(0.029)	(0.042)	(0.036)
Treated * Post-2003	-0.149***	-0.170***	-0.049	-0.063***	-0.048	-0.042
	(0.044)	(0.034)	(0.033)	(0.021)	(0.045)	(0.029)
Mkt Power	-0.051***	-0.492***	0.551***	-0.656***	0.562***	-0.730***
	(0.008)	(0.011)	(0.017)	(0.011)	(0.035)	(0.022)
Mkt Power * Treated	0.216***	0.032	0.064*	0.080***	0.020	0.048*
	(0.032)	(0.026)	(0.035)	(0.020)	(0.046)	(0.027)
Mkt Power * Post-03	0.047***	0.294***	-0.197***	0.289***	0.045	0.292***
	(0.011)	(0.013)	(0.024)	(0.015)	(0.055)	(0.033)
Mkt-Pow*Treat*Post-2003	0.072	-0.017	0.114**	-0.016	-0.116	0.019
	(0.052)	(0.040)	(0.052)	(0.030)	(0.072)	(0.042)
Constant	2.883***	-0.283	2.741***	-3.991***	2.475***	-5.267***
	(0.091)	(0.532)	(0.133)	(0.523)	(0.110)	(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 1.10: Robustness Checks for Pigou's E for Production Workers

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

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

CHAPTER 2

IMPACT OF FIRING RESTRICTIONS ON FIRM PERFORMANCE: EVIDENCE FROM INDONESIA

2.1 Introduction

One of the main goals of governments in enacting firing restriction legislation is to protect the workers from unstable employment situations. On the other hand, employers would like the freedom to adjust their inputs freely to deal with changes in demand, and the presence of firing restrictions shifts some of the adjustment burden on to the other inputs (capital, intermediate inputs, etc.). Proponents of increased firing restrictions are changing the relative prices of the different ways firms[1] can adjust their inputs. These proponents base their argument on negative externalities associated with the firing that the firms do not directly bear. Not only are there significant economic costs to the person losing their job, but there also psychological and sociological impacts to the person as well. From the perspective of the firm, there are adjustment costs if there is firm specific training required for the worker to reach full productivity, though the change in legislation should not have direct impact on the firm's response to these productivity based adjustment costs. This paper investigates the impact of the government's changing the relative costs of adjustment to the firm on the behavior of the firm and the resulting impact on the workers. The firm outcomes that this paper will analyze include employment, wages, output, and input mix.

[1]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.

There have been studies analyzing the impact of firing restrictions, however, this study adds to the literature in three ways. First, this study uses micro-data from the manufacturing sector of Indonesia. Abowd and Kramarz (2003) were the first to use micro-data, and Heckman and Pages (2004) note the importance of using micro-data when studying this issue as opposed to the cross-country analysis that has been common. Second, this study focuses on the impact of the firing restrictions on the firm, where many studies have used household or individual level data. While it is important to study the impact of the firing restrictions on the workers, the impact of firing restrictions on the firm has been relatively understudied. Finally, this paper analyzes the impact of a specific policy change in Indonesia, as compared to many studies that have more abstract measures of rigidity, such as a strictness ranking or the number of laws that were passed for or against more flexible labor markets.

The change to the labor law in Indonesia was a large piece of legislation (Manpower Law 13/2003) that contained many provisions. The three most controversial areas dealt with severance pay, the use of contract workers, and the setting of minimum wages (Manning and Roesad 2007). Manning and Roesad state that the provisions on severance pay were the most criticized aspects of the law, and my informal conversations with human resources personnel confirmed that the severance pay component of the law was very burdensome to the way they conducted their operations. Severance pay is especially important in the context of Indonesia as it is the primary source of unemployment benefits for most wage workers (Manning and Roesad 2007). The severance payouts are based on the workers' wages, so any changes to minimum wages would also carry through and affect the severance payout. Most firms respond to the increased severance payouts by increasing their use of contract workers, but the legislation made it more difficult to do so by limiting the types of activities contract workers were permitted to do and by limiting the length of their contract (to a total of three years, after all possible renewals and extensions). Increases in the minimum wage would have a similar predicted impact on the firm as the increases in severance payments, as both policies increase the cost of labor. I have data on the prevailing minimum wage in each province in each year, and will use that control for the impact of the minimum wage in the empirical analysis.

The changes to severance payouts may also be the most proximate change for the empirical analysis. The law regarding severance payouts took effect immediately in 2003 when the law was passed. However, the impact of the changes to minimum wages and to the regulations for contract workers may have been more delayed. The labor law made two changes to the minimum wage, decentralizing the setting of the minimum wage to the districts and changing the criteria upon which the minimum wage is set. Thus, the law did not change the minimum wage itself, just the process for how the minimum wage was set. Also, the law did immediately change the regulations for contract workers, but the three year limit for using a specific contract worker would have a delayed impact on the behavior of the firm. So, the delayed impact of components of the law, and the controls for the local minimum wage together help me parse out the impact of the increased severance payment on the firms.

This study is important as many developing countries have recently adopted similar pieces of legislation or have had debates about doing so. Indonesia has had significant debates about reforming this law as many companies contest that the law is too restrictive. Reforms that would have weakened the regulations were almost passed in 2006, but popular support amongst the working class prevented the law from passing. This research will help inform the debate as it provides information about the impact of a specific regulation on the performance of firms using micro data.

The next section will review the previous work that has been done on this topic. Section three will describe the empirical methods used in the analysis. Section four describes the data and section five presents the results. Section six performs some robustness checks, and the last section concludes and provides some policy implications.

2.2 Literature Review

Many studies have looked at the impact of firing restrictions on the labor markets both in developed and developing countries. The three main outcomes the studies have analyzed are labor turnover, employment levels, and the unemployment rates of the local labor market. Bertola (1990) and Bentolila and Bertola (1990) develop dynamic partial-equilibrium models which predict that firms will reduce turnover, both hiring and firing, in the face of increased firing restrictions. However, the impact on the level of employment, and thus unemployment, depends on whether hiring or firing is reduced more. The literature has found mixed results for the impact of severance restrictions on both employment and unemployment. Both Heckman and Pages (2004) and Addison and Teixeira (2001) provide good summaries of the studies that find a negative relationship between job security provisions and employment, and also those that find no evidence of such a relationship. Similarly, studies have found mixed results regarding the relationship between job security provisions and unemployment. Most of the studies characterized in these reviews use aggregate data from developed countries, predominantly the OECD countries. Blau and Kahn (2002) provide a thorough analysis of the US labor market and how it compares with other OECD countries.

A prominent study using data from a developing country is Besley and Burgess (2004). They looked at changes in labor laws in India by state, and how the different labor regimes impacted aggregate output, employment, investment, productivity and poverty. They used counts of laws for or against a more flexible labor force and found that more pro-firm laws helped firms and reduced poverty, while more laws protecting workers increased poverty.

Heckman and Pages highlight the need for using micro data from single countries. While it is not necessary for these data to come from developing countries, developing countries often are good contexts to study as there are large changes in job security provisions either over time or across regions, providing the necessary identifying variation. Four such studies are Kugler (2004), Adhvaryu, Chari, and Sharma (2010), Mondino and Montoya (2004), and Saavedra and Torero (2004).

Kugler uses micro data on households in Columbia. She uses a difference-in-differences technique, and also estimates an exponential duration model. She finds that job security provisions decrease turnover and increase unemployment.

Adhvaryu et al build on the Besley and Burgess study by investigating whether firms in Indian states that have more restrictive firing laws are able to adjust their labor more or less in response to demand shocks. Using rainfall shocks as their exogenous variation, they find that firms in less restrictive states are more able to adjust their employment levels. This finding is consistent with the standard theoretical prediction.

The other two studies, Mondino and Montoya, and Saavedra and Torero, use similar methodologies on disaggregated firm level data from Argentina and Peru, respectively. They estimate labor demand equations in which a direct measure of the costs of job security is used as a control variable. This measure is constructed based on the labor taxes firms are required to pay, and the structure of the severance payment schedule. Both studies find a negative relationship between job security and employment. One weakness of these studies, which the authors admit, are the aggregate instruments used to identify the impact of job security at the firm level.

My research continues the recent trend of using firm level data, though it builds on the literature by analyzing a specific policy change. This will provide more focused insight as how a specific job security provision impacts firm behavior. Also, the difference-in-differences approach follows well established methods for how to identify the impact of the policy.

Two other important papers in this literature are Abowd and Kramarz (2003) and Autor (2003). Abowd and Kramarz investigated the existence and magnitude of the hiring and separation costs faced by French firms in 1992. They found that there were virtually no variable hiring costs, except when hiring highly skilled workers on long-term contracts. They also found that the separation costs were significantly positive, and consisted of large fixed components, indicating that more adjustment should be done on the hiring side and that separations should be done in bunches. Autor (2003) looked at changes in ”Employment at Will” laws on the use of temporary labor and found an increase in the use of temporary labor in states that have imposed restrictions on Employment at Will doctrine.

2.3 Empirical Approach

Basic economic theory has some straightforward predictions for the impact of increased firing restrictions on firm behavior. The predictions come from the standard representation of a firm’s production function,

$$Y = AK^{\alpha}L^{\beta},$$

where Y is firm output, K is capital, L is labor, and A is a productivity term. The capital and labor shares are represented by α and β, respectively. The overall impact of the labor law is to increase the cost of labor. This will cause the firm to use less of that more expensive input, L, and more of the other input, K. However, the law restricts the ability of the firm to reduce its workforce, restricting the negative effect on L, so the overall prediction for L is ambiguous. The increased costs of production will also lead to lower output. The direct effect of the policy on labor costs is to increase them, though if enough firms decrease the amount of labor employed, there could be a general equilibrium effect dragging down wages for workers.

To understand the impact of the increased firing restrictions contained in Manpower Law 13/2003, this analysis will use a difference in differences technique around the implementation year of 2003. I will use the firms that were more likely to comply with the law as the treatment group and the firms that were not as likely to comply as the control group. Since the control group will be exposed to the treatment to some extent, the measured impact of the policy change will be combined with the difference in exposure to the law. This combined measurement will be an underestimate of the overall impact of the policy. There are two different dimensions across which there might be differences in compliance with the labor law by firms. The first is by firm size, with large firms being more likely to comply and small firms being more likely to slide under the radar. Secondly, firms closer to the enforcement office will be more likely to comply.

There is some research documenting the likelihood of compliance amongst Indonesian firms. Harrison and Scorse document that manufacturing firms exposed to foreign interests are more likely to comply with minimum wage laws (2004 and 2010). They measure foreign influence separately through foreign ownership and the amount a firm exports. Manning and Roesad also argue that large firms and foreign-owned firms in Indonesia are more likely to be held in compliance to labor laws (2007). Large firms tend to have greater foreign exposure, which supports the identification of the first treatment group. I also explicitly do not include foreign owned firms in the control group as predicted impact on them would be mixed.

There have also been other studies that have used firm size as a determinant in compliance with Labor Laws. Chay (1998) studied the impact of extending the Equal Employment Opportunity Act to small firms, and found that the EEOA had a positive effect on the labor market status of African-Americans. Carrington, McCue and Pierce (2000) looked at the differential impact of Title VII of the 1964 Civil Rights Act to employers of different sizes. They found that minorities moved to larger employers after the passage of the law. While both of these studies examined laws that had specific exemptions for small firms, they provide support for the argument that governments have different expectations for compliance for firms of different sizes.

Therefore, the first primary treatment group will be large firms and the corresponding control group will be small domestically-owned firms. I exclude the small foreign owned firms from the analysis as the predicted impact for them is mixed. I also repeat the analysis using a second identification strategy,identifying the treatment group as firms located in districts which are the provincial capital. The assumption is that the government is more likely to enforce the new labor laws on the firms to which it has easy access. The control group is then firm located in districts which are not the provincial capital [2].

The difference in differences methodology can be represented in the following manner.

$$Y_{it} = Treat_{it} + Post_{it} + \alpha Treat * Post_{it} + X_{it}\beta + \epsilon_{it} \tag{2.1}$$

Where Y_{it} is the outcome variable for firm i in year t. $Treat$ is a dummy variable equal to 1 if the firm is a member of the treatment group, and zero otherwise. $Post$ is a dummy variable equal to 1 if the observation is after the program has been implemented. Then $Treat * Post$ is the interaction of the two dummy variables, which will only be equal to 1 for firms in the treatment group after the policy has been implemented. X_{it} is a vector of k control variables, with β being a vector of k coefficients. The last term, ϵ_{it} represents the error term. In this setup, α captures the impact of the policy change. The analysis below will present results from a base specification with only year, region, and industry dummies, and then an additional specification which also includes additional

[2] I assign all districts in the province of Jakarta to be in the treatment group.

controls.

The identifying assumption in this approach is that, conditional on a set of control variables, the only change between before 2003 and afterwards for these two groups is the change in the labor laws. The main threat to identification in difference-in-differences analysis is that the treatment and control groups are experiencing different trends leading up to the policy change. If the groups experience different pre-treatment trends, the control group's behavior after the policy change is no longer a valid counterfactual for treatment group. To check for this issue, the analysis below will display the trends for the variables of interest over the study period.

The first approach used in this analysis will compare large firms to small domestically-owned firms. I follow standard practice and define large firms as those with at least 250 employees, and small firms as those with less than 50 employees [3]. Medium sized firms are excluded from this analysis. The control group also excludes foreign-owned firms, and again I follow standard practice by considering a firm to be foreign owned if at least 10% of its capital is foreign owned. This strategy is based on the assumption that large and small firms would have followed the same trends in the absence of the law change, which might be rather strong as the average large firm is quite different from the average small domestically owned firm.

Therefore, I consider a second, complementary approach, defining the treatment group as those firms located in the same district as the provincial capital. The motivation behind the approach is the same, that some firms are more likely to comply with the law than others. This second approach also allows

[3] As a robustness check, I consider small firms to be those with less than 30 employees, and large firms to have at least 100 employees.

me to consider a refinement of the difference in differences methodology proposed by Blundell and Costa-Dias (2000). They suggest matching each firm in the treatment group to the most similar firm in the control group. This changes the assumption to say that the firms in the control and treatment groups that are most similar in terms of their observables are also most likely to be similar in their unobservables. To implement this, I use a probit regression to predict the probability that each firm is located in the district with the provincial capital, and then match each treated firm with three firms not in a district with a capital, but had the closest probabilities to being located there. This matching approach improves on the standard difference in differences methodology by more strategically defining the control group which will have more similar trends in unobservables.

Firms are allocated into treatment and control groups based on their average values for the pre-treatment period (2000-2002). Also, the observations from 2003 are not used in the analysis to provide a more clear distinction between the before and after environments. The law became effective in March of 2003 which means I might miss some of the short term responses of firms, but I am more interested in the long term responses of the firms. This is partly because my data is not granular enough to study the short term effects, but also because the longer term responses provide evidence of the structural changes that have occurred in the labor market.

Bertrand, Duflo, and Mullianathan (2004) also discuss an issue with using difference-in-differences techniques. They show that many effects may be erroneously shown to be significant because of the serial correlation in analyzed variables. However, their Monte-Carlo simulations shows that this issue be-comes less significant as the number of years used in the analysis shrinks. One of their recommendations for dealing with this issue is to flatten the data by separately pooling all of the years together before and after the policy change. With only six years of data used in my analysis, this issue does not pose too much of a threat.

Another concern about drawing inference from difference-in-differences analysis based on ordinary least squares is a concern here. Donald and Lang (2007) demonstrate that the standard asymptotics are not valid when the number of groups is small. There are only two groups in this analysis, the treatment group and the control group. They propose a two-step procedure that provides unbiased estimates for the variances of the coefficients. However, they also state that if there are large numbers of observations within each group, which is the case here, that feasible GLS estimation will produce unbiased estimates. Therefore, I use feasible GLS estimation in each of the specifications reported below.

2.4 Data

The data I use for this analysis is Indonesia's Annual Manufacturing Survey, *Survei Tahunan Perusahaan Industri Pengolahan*. It is a census of all the manufacturing establishments in Indonesia with at least 20 employees. The firms are required to fill out the survey each year, and I have data covering years 2000-2006. This panel dataset includes many variables, but importantly for this study, it has data on output (revenue), inputs, capital, wages, number of employees, ownership, location, industry, etc. A few years of data have more detailed information, such was the education level of the workforce, or the percent of output exported. I include some of these variables in the summary statistics for informational purposes, but because of the variables' inconsistent availability I do not include them in the analysis.

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 1USD. 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. Observations were considered invalid if they were percentage variables with values outside the range 0-100, for example a firm with 320 percent of its output exported. Missing values were cleaned if they were surrounded by actual values in both the previous and following years. Observations were considered to be outliers if they were significantly different from both the previous and following values. I followed the Hallward-Driemeier and Rijkers thresholds for determining when observations were significantly different. In each of these cases, observations were replaced with the mean of the corresponding values from the previous and following years. When an observation was on a boundary, only the previous or following year was used for cleaning purposes. If suitable neighbors were not found, the missing or invalid data was left in the sample.

I have data on the number of production workers and non-production workers. Production workers are those working in the production activities of the firm, and non-production workers comprise everyone else, such as management and administrative staff. Since over 84% of workers are production workers, I focus the analysis on them. The data also contains information on total salary and benefits paid to workers. I add these together to construct the total labor costs to the firm, and then divide by the number of workers to yield the average wage paid by the firm to each of its workers. However, I will also use the salary and benefits components of wages as distinct outcome variables to see if the policy change had a differential impact on the various components of worker pay. Theory would predict that the law change required the benefits portion to increase, so the firm would compensate by decreasing the salary component, to keep the overall labor cost the same.

Summary statistics for the data can be found in Table 2.1. Each observation is a firm-year. Summary statistics for all firms are found in the first column. The next column contains statistics for all large firms (at least 250 employees), the third columns shows the means for firms that are both small and domestically owned. The second and third columns comprise the treatment and control groups for the first approach to identifying the treatment and control groups for the analysis. Column 4 then shows the summary statistics for all firms in districts which also have the provincial capital. These firms are the treatment group for both the second and third set of analyses. The control group for the second approach are firms not located in the district with the provincial capital, and these results are shown in column 5. The last column shows the summary statistics for the matched control group, firms not in the district with the provincial capital, but have a high predicted probability to be located there.

The first row shows the continuous version of the foreign ownership variable, and it shows that large firms do have greater foreign ownership. Also, firms that are classified as not being foreign owned may still have a small bit of foreign influence, though it appears to be minor. There are large differences in the averages reported in columns 2 and 3, which suggests that while there may be different levels of compliance between the large and small firms, there are many other differences which may preclude a clean analysis of the treatment effect. There are not as large of differences between the treatment and control groups as identified by their proximity to the provincial capital. These results are shown in columns 4 and 5. The firms near the provincial capital are older, smaller, export less, have greater revenues, and pay higher wages. The matched control group in column 6 shows means which are closer to the treatment group, which shows the matching process has selected firms which are more like those in the treatment group.

2.5 Results

This analysis will primarily focus on four outcome variables that measure outcomes for the various sides in the debate over firing restrictions. I use the natural log of firm revenue to measure the impact of firing restrictions on the firm. I use the number of production workers employed by the firm and average wages paid by the firm to production workers as measures of how the policy impacts the labor market. I also look at how the policy impacts the capital-labor ratio of the firm, to measure how much firms are able to substitute capital for labor after the costs of labor are increased. I use the employment and wages of production workers as they comprise the majority of the workforce, and are the ones most likely impacted by the policy change. I also break down the impact of the policy on the salary and benefit components of wages.

As discussed above, when using difference in differences analysis, it is important to compare the trends of the groups before the policy change. In order for the analysis to work, the pre-treatment trends facing the treatment and control groups need to be similar. These trends are displayed in Figures 1-3 for the six outcome variables. In each panel of the figure, the trends are displayed for the both the treatment and controls groups relative to the mean value for each outcome in the first year used in the analysis, 2000. Figure 1 shows the results using the identification approach based on firm size. Figure 2 shows the results for the identification based on location, and Figure 3 uses the matched control group.

I will walk through the figures for each outcome variable, starting with the output (revenue) of the firm. In all three identification strategies, the pre-treatment trends for the treatment and control groups track each other pretty well. The trends then start to separate in 2003 in both Figure 1 and 3, with the treatment group having smaller increases in output than the control group. This negative impact of the policy on the output of the firm coincides with the theoretical prediction, however this analysis is of unconditional trends, and there may be other characteristics of the groups that could explain the change in output.

The second outcome is employment, which is found in the upper right corner of each figure. Figure 1 shows a discrepancy in 2001, but also that the trends are moving in opposite directions from 2003 onwards. Figures 2 and 3 show trends for the treatment and control groups tracking each other, but starting to separate in 2002, with the control group having lower levels of employment growth. This early break in the trend is cause for concern, and suggests that the environment for the two groups changed for a reason different from the law change. Its also possible that the treatment firms were anticipating the law change, and reducing their workforce before it became more expensive to do so.

The third outcome is wages, the sum of salary and benefits. For this variable, all three figures show a similar pattern, with wages growing faster for firms in the treatment group, however the trends started to separate in 2002. This could also be due to the firms anticipating the law change. If firms were indeed anticipating the policy change, and not responding to some other event, the difference in differences results reported below will understate the overall impact of the policy. The bottom row of each figure shows the breakdown of wages into salary and benefits. The trends for salary closely match that for the total wage, which is expected as salary is the major component of wages for these workers. The trend shown in Figure 1 shows benefits decreasing in the treatment firms, which is counter to how we would expect firms to respond to the policy. Though, this is just the unconditional trend. The important point to note here is that the trends started to separate in 2002, supporting the idea of firms anticipating the law change. The trends in benefits in Figures 2 and 3 show the trends tracking each other pretty well, until 2006, when the treatment group has a dramatic decrease in benefits, which could potentially skew the analysis.

The last variable to consider is the capital-labor ratio. The trends for this variable are pretty similar in all three figures, with a separation in the trends starting in 2002, the year before the policy change.

The simplest way to conduct difference-in-differences analysis is to compare the means for the treatment and control groups both before and after the policy change. However, these results do not account for any differences in the distribution of firms across industry or region, nor do they control for any firm specific variables that may be directly impacting the outcome. To condition for these other variables, equation 1 is estimated via ordinary least squares. The results of these regressions are reported separately by outcome variable in Tables 2.2-2.7. In each table, the first two columns report the results using the identification approach based on firm size. The third and fourth columns report the results using firm location to identify the treatment and control groups, and the last two columns using the matched control group. In each table, the odd numbered columns report the results using only year, industry, and region dummies as controls in the regression[4], whereas the even numbered columns include additional controls. The additional controls used are based on a standard production function formulation, and depend on which outcome is considered.

Table 2.2 displays the results for firm output. The prediction is that the increased severance payments would reduce firm output as firms need to adjust to the increased labor costs. The impact of the policy is captured by the coefficient on the interaction term, $Treated * Post - 2003$. In the first two columns, there is a negative and statistically significant coefficient, confirming the theoretical prediction. However, the results in columns 3 and 4 yield positive and statistically significant results. These conflicting results say that large firms in-

[4]There are 32 regions and 20 two-digit industries.

crease their output more slowly than the small-domestically owned firms, but the firms located in the same district as the provincial capital increase their output more so than the firms located in other districts. One explanation for these results is that the firms located in the provincial capital are smaller on average than the other firms. So in both approaches, the group with smaller firms had the higher growth in output.

The last two columns in Table 2.2 report the results by location, but using the matched control group. The treatment effect in these regressions is insignificant. This analysis is potentially superior to the approach used in columns 3 and 4, as the control group is strategically constructed to be a more appropriate counterfactual. In this case, the policy positively impacts output in firms located in the provincial capital as compared to all other firms, but has no impact as compared to firms in other districts that are most similar to the firms in the capital. However, neither of the geographical approaches supports the theoretical prediction of the increased labor costs leading to decreased output.

I next examine the impact of the increased severance payments on the number of production workers employed at each firm. These results are reported in Table 2.3. In all six regressions, the treatment effect is negative, and is statistically significant in 5 of the specifications. The theoretical prediction for the impact of job security provisions on employment is ambiguous, but these results show that for firms in the manufacturing sector in Indonesia, the overall impact of the policy on employment is negative. A common explanation for this type of result is that it's due to firms decreasing their hiring more than they decreased their firing. The magnitude of these coefficients suggest that the policy reduced employment of production workers about 5 or 6% (focusing on the results including the additional controls).

The third outcome variable is the average wage the firm pays their production workers. These results are reported in Table 2.4. In all six specifications, the treatment effect is positive, which supports the predicted impact. The law change mandates an increase in the benefits firms are required to pay their workers. While firms could reduce the salary portion of the wages to compensate for the increased benefits, leaving the overall cost the same, it is often very difficult for firms to reduce wages as workers dislike paycuts. The size of the impact of the policy change is about a 4 to 8% increase in wages.

As mentioned above, this policy change might impact the salary and benefit components of wages differently. This prediction analyzed in Tables 2.5 and 2.6, with Table 2.5 showing the impact on salary and Table 2.6 showing the impact on benefits. One potential issue with this analysis is that while the firms are supposed to set aside funds to be prepared to pay workers their severance payments, it is possible that firms do not report these funds in the benefits portion of the survey. Table 2.5 reports a positive treatment effect in all six specifications, whereas Table 2.6 has mixed results for the effect on benefits.

The positive impact on salary could be due to the changes in the minimum wage law which were also a part of Labor Law 13. However, I include controls for the minimum wage in the province in each of the even columns, and the positive treatment effect on salary remains[5]. The minimum wage increases steadily throughout this period, though there is not a break in the trend in 2003. However, the minimum wage data is only at the provence-year level, and may be missing some of the changes at the district level that were enabled by the law

[5]I thank David Newhouse at the World Bank for generously providing the minimum wage data.

change.

The first two columns of Table 2.6 report a negative relationship between the policy and benefits, but the other four columns report positive effects. The predicted impact is positive, so the negative coefficient is troubling. It could be that the large firms have some other factor influencing the amount of benefits they pay, such as a decrease in health care costs.

The last outcome variable considered is the capital-labor ratio, and these results are report in Table 2.7. The treatment effect is positive and statistically significant on all six specifications, though the magnitude of the coefficient varies some. The positive effect is consistent with the theoretical prediction, that firms would use relatively more capital and less labor as the cost of labor increases. The magnitude of the effect ranges from 8% to 25%.

I performed a few variations on the above analysis to check the robustness of the results. These results are reported in Table 2.8. The specifications are the same as those used in the main results, however, the table just reports the results for the coefficient on the treatment effect. The first check I consider was to assign firms to the treatment and control groups based on their size in a different year. The main analysis assigned firms based on their average size between 2000-2002, however its possible that the firms were anticipating the law change and adjusting their size prior to the law being passed. The trends shown in the figures above support this possibility since the trends start to separate in 2002, the year before the law was implemented. To check the sensitivity of the year of assignment, I assign firms based on their size in the year 1999. These results are reported in the first two columns. Column 2 includes all of the controls, and the all of the signs of the results match the main results above, though the negative effect on employment is no longer significant.

The next check I perform is to assign firms to treatment and control groups using different size cutoffs. The main analysis considers small firms to have less than 50 employees, and large firms to have at least 250. Here I consider small firms to have less than 30 employees, and large firms to have at least 100. A firm with 100 employees is a good sized firm, and may be big enough to be on the radar of the local labor inspector. It is also important to note that firms with less than 20 employees are not included in this data, so the control group here consists of firms with 20 to 30 employees. The results using these smaller cutoffs are reported in columns 3 and 4. The sign of the coefficients in column 4, which include all of the additional firm controls, match the main results, however the coefficient for the impact of the policy on employment is no longer significant. This suggests that the employment result report above is sensitive to the specification chosen.

The last check considers a variation on the second identification approach, considering firms to be treated not only if they are in the same district as the provincial capital, but also if they are in a neighboring district. These results are presented in the last two columns of Table 2.8. The signs of the coefficients in column 6 match the main results, except for the coefficient on output. The main output results were mixed, with the identification based on firm size reporting a negative relationship, but the identification based on location reporting a positive coefficient. So, the positive result in the robustness check, using all firms near the capital, supports the result based on firm size.

2.6 Conclusion

This paper has used difference-in-differences analysis to study the impact of a package of labor laws implemented in Indonesia in 2003. The most significant changes in the law increased firing restrictions, decentralized minimum wage setting, and placed restrictions on how contract workers could be used. I used data from Indonesia's census of manufacturing firms from 2000 to 2006 to analyze the impact of the law on the behavior of firms and the labor market. To establish treatment and control groups for the analysis, I argued that some of the firms were more likely to comply with the law than others, whether through their own volition or through government enforcement.

I considered two dimensions along which compliance may differ, firm size and firm location. The first approach assumed that large firms complied with the new law, whereas the small, domestically owned firms did not. The second approach assumed that firms located in the same district as the provincial capital were more likely to comply with the new law, whereas firms in other districts might not.

The results showed that the policy had a negative impact on firm output when identifying the impact by firm size, and no impact when using the matched control group. There was a positive effect on the wages of production workers and on the capital-labor ratio of the firm. There were mixed results on the employment of a firm, with the main results reporting a negative effect, though the result was sensitive to the specification assumptions. There were also mixed results for the impact on firm output and the benefits paid by the firm. These results suggest that firms are trying to transition towards relatively more capital intensive production processes. As the firms transition, however, their output levels are about 4.5% less than what they would have been had the law not been enacted. The law is not having a negative impact on the wages of workers however, as the wages paid to production workers increased somewhere between 4 and 8%.

This work provides relevant information to the policy discussion about the impact of job security provisions on both sides of the labor market. While wages are increased for production workers, the number of workers employed may fall. Also, there is a negative impact on the output of firms, which may disappear in the long run as firms adjust their input mix, but the international firms may also move to other lower cost countries. More work needs to be done to quantify the magnitudes of these various effects.

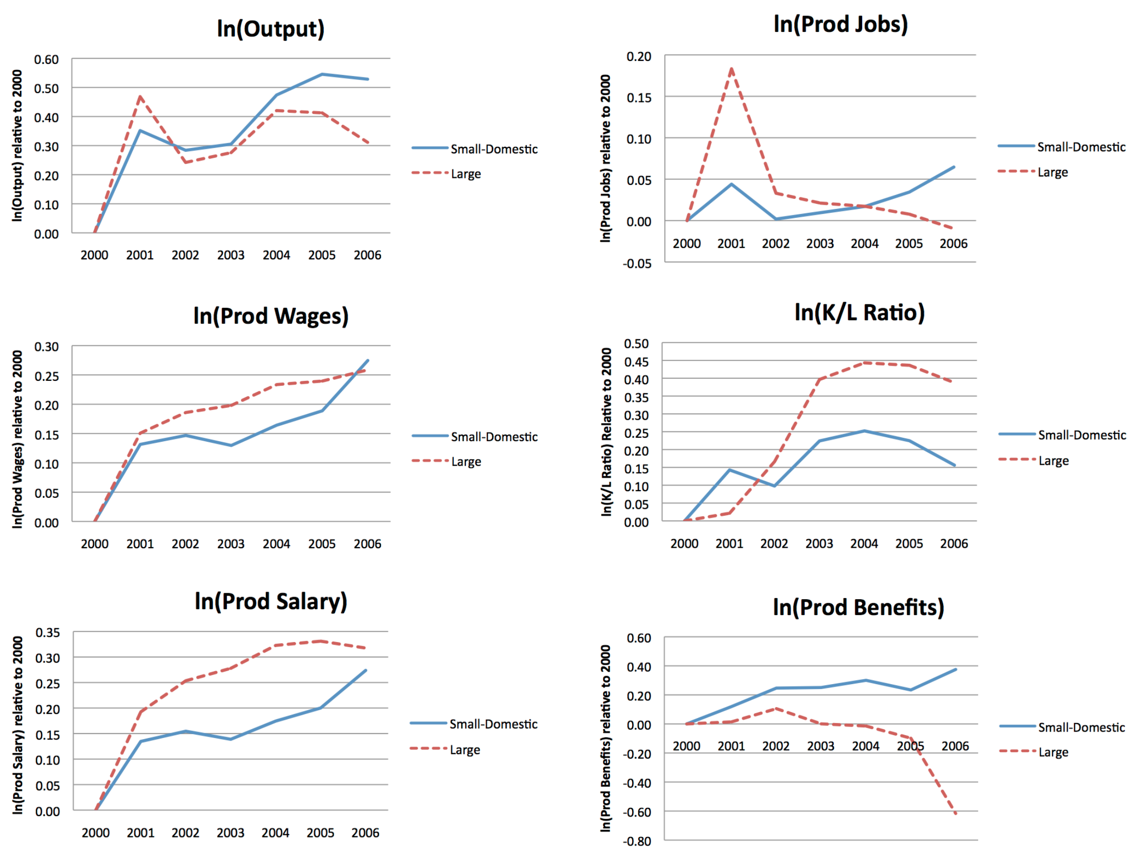

Figure 2.1: Trends in Outcome Variables Separated by Firm Size

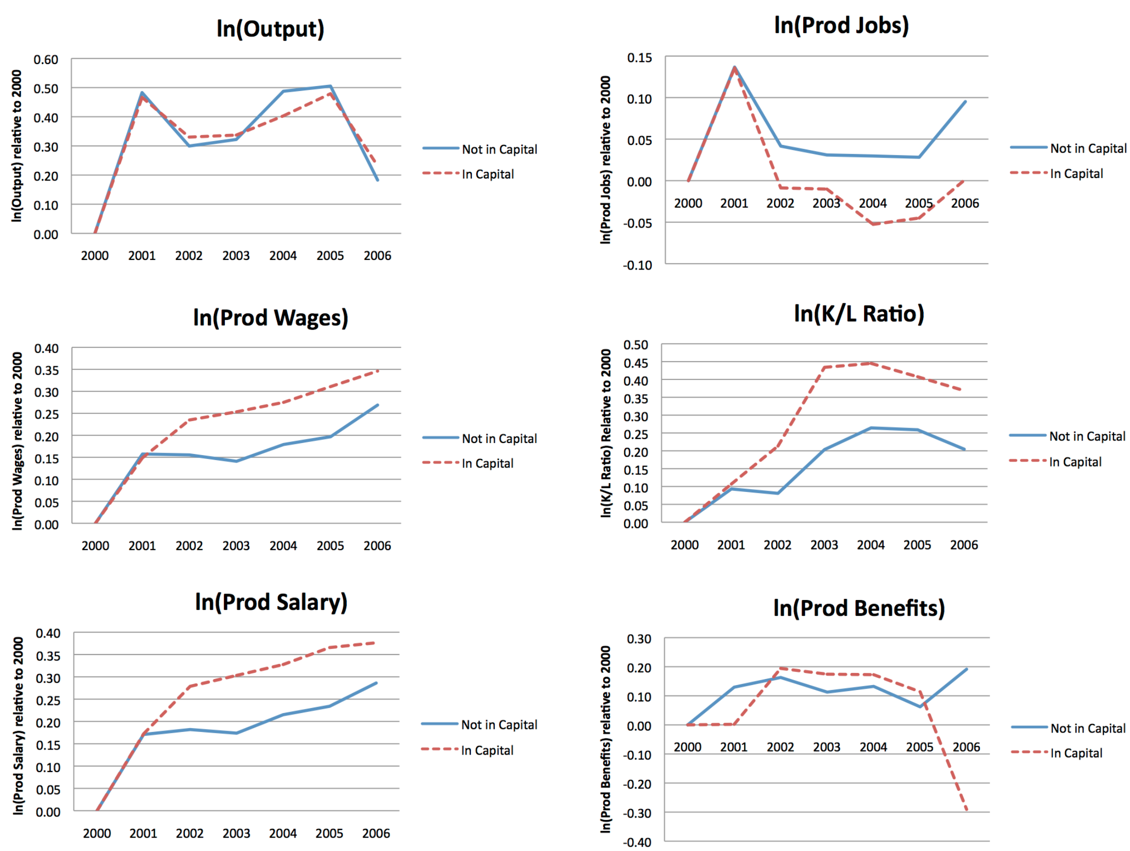

Figure 2.2: Trends in Outcome Variables Separated by Firm Location

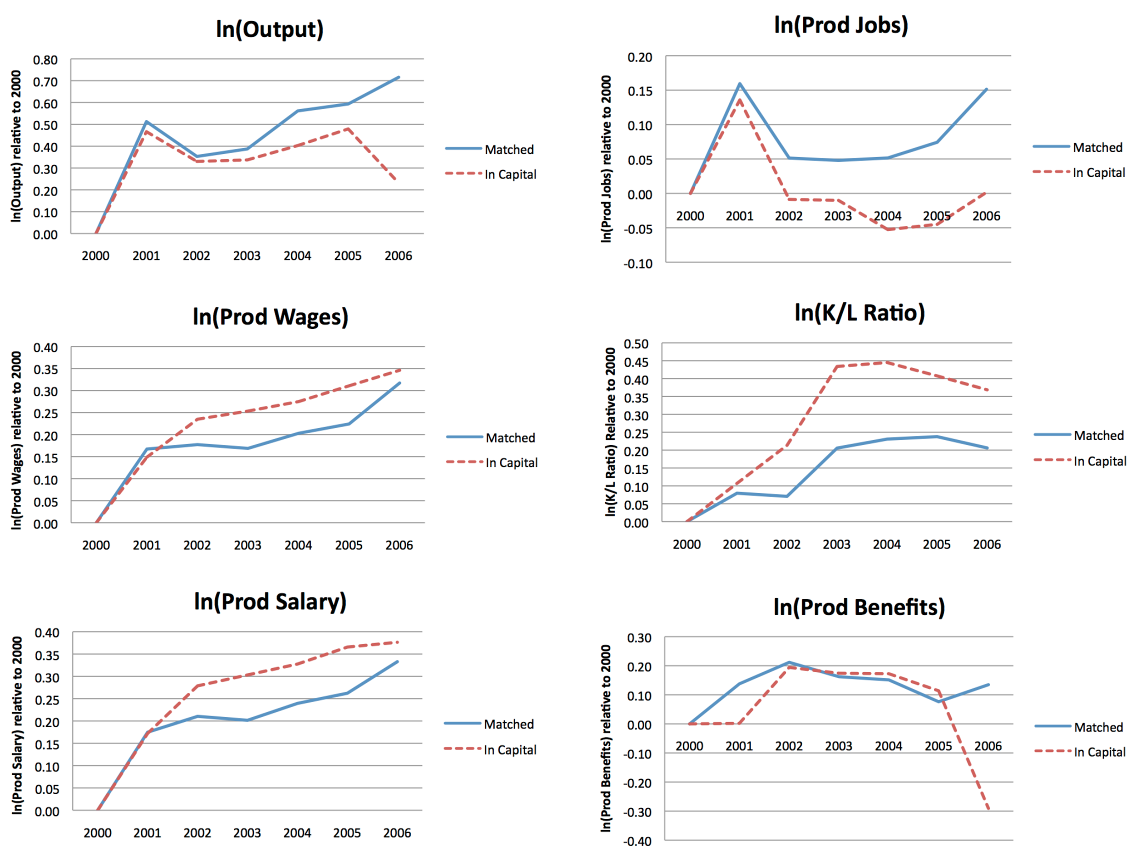

Figure 2.3: Trends in Outcome Variables Separated by Firm Location with a Matched Control Group

Table 2.1: Summary Statistics of Indonesian Manufacturing Establishments

	All Firms (1)	Large Firms (2)	Small-Dom Firms (3)	In Capital (4)	Not In Capital (5)	Matched Firms (6)
%Foreign	5.80	15.86	0.09	5.01	6.04	6.16
Output (Bn-Rph)	25.36	106.37	1.60	28.04	24.53	26.88
Input (Bn-Rph)	15.95	65.54	1.05	17.23	15.56	17.99
Investment(Bn-Rph)	1.89	4.42	0.23	1.01	2.16	1.98
Capital(Bn-Rph)	14.82	44.57	0.76	8.66	16.76	14.18
% Exported	12.99	28.65	5.89	11.20	13.54	12.13
R&D Exp.(Mn-Rph)	5.01	24.99	0.24	6.48	4.55	5.87
VA/L (Mn-Rph)	31.04	46.86	17.62	34.04	30.10	33.61
Age	16.94	18.32	16.82	17.78	16.66	17.06
#Emp	193.66	774.40	29.93	179.45	198.06	198.46
%Prod	84.41	84.64	85.64	82.83	84.89	83.14
Wage - Prod (Th-Rph)	5,036	6,313	4,204	5,929	4,759	5,193
Wage - Non-Prod (Th-Rph)	10,638	18,841	6,211	11,829	10,243	11,115
Prod Salary (Th-Rph)	4,503	5,377	3,901	5,322	4,249	4,584
Prod Benefits (Th-Rph)	435	819	218	485	420	536
Num	139,043	25,944	60,795	32,897	106,146	20,191

Notes: All values are in constant 2000 Rupiah. Data covers years 2000 - 2006. The export data is available for years 2000, 2004, and 2006. The R&D expenditure information is available for a few firms in years 2000 and 2006.

Table 2.2: Difference in Differences Results for Firm Output

	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	3.655***	0.376***	0.202***	0.105***	0.144***	0.069***
	(0.020)	(0.027)	(0.024)	(0.013)	(0.031)	(0.017)
Post-2003	0.239***	0.180***	0.163***	0.363***	0.231***	0.507***
	(0.019)	(0.023)	(0.023)	(0.033)	(0.044)	(0.062)
Treated * Post-2003	-0.110***	-0.045**	0.052*	0.046***	-0.015	0.036
	(0.029)	(0.020)	(0.031)	(0.017)	(0.042)	(0.024)
ln (Min Wage)		-0.051		-0.108**		-0.230***
		(0.057)		(0.047)		(0.068)
ln (Total Jobs)		0.992***		1.079***		1.145***
		(0.009)		(0.005)		(0.007)
ln (Capital)		0.198***		0.219***		0.180***
		(0.004)		(0.003)		(0.005)
constant	14.903***	8.784***	15.379***	9.275***	14.332***	10.578***
	(0.172)	(0.764)	(0.223)	(0.600)	(0.272)	(0.864)
r2	0.673	0.797	0.157	0.730	0.110	0.726
N	52,006	51,731	84,547	84,052	31,868	31,808

Notes: Standard errors are in parentheses. The sample consists of all treated and control firms for the years 2000-2002 and 2004-2006. All models include year, region, and industry effects.

Table 2.3: Difference in Differences Results for Employment

	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	2.707***	1.695***	0.045***	-0.050***	0.051***	-0.016
	(0.011)	(0.016)	(0.015)	(0.009)	(0.019)	(0.012)
Post-2003	0.051***	-0.001	0.080***	-0.115***	0.106***	-0.182***
	(0.009)	(0.012)	(0.015)	(0.027)	(0.029)	(0.036)
Treated * Post-2003	-0.085***	-0.065***	-0.020	-0.048***	-0.060**	-0.061***
	(0.017)	(0.014)	(0.020)	(0.012)	(0.027)	(0.017)
ln (Min Wage)		-0.078**		-0.039		0.035
		(0.031)		(0.032)		(0.046)
ln (Capital)		0.036***		0.084***		0.077***
		(0.002)		(0.002)		(0.003)
ln (Output)		0.249***		0.429***		0.451***
		(0.003)		(0.002)		(0.003)
Constant	3.437***	0.313	4.795***	-3.237***	4.579***	-4.034***
	(0.081)	(0.408)	(0.124)	(0.407)	(0.169)	(0.590)
r2	0.794	0.850	0.103	0.653	0.085	0.666
N	51,998	51,724	84,539	84,045	31,864	31,804

Notes: Standard errors are in parentheses. The sample consists of all treated and control firms for the years 2000-2002 and 2004-2006. All models include year, region, and industry effects.

Table 2.4: Difference in Differences Results for Wages of Production Workers

	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.390***	-0.269***	0.121***	0.091***	0.125***	0.108***
	(0.007)	(0.010)	(0.006)	(0.006)	(0.008)	(0.008)
Post-2003	0.043***	-0.008	0.031***	0.138***	0.029**	0.223***
	(0.008)	(0.011)	(0.007)	(0.015)	(0.012)	(0.028)
Treated * Post-2003	0.020**	0.037***	0.090***	0.082***	0.068***	0.069***
	(0.010)	(0.009)	(0.008)	(0.007)	(0.012)	(0.010)
ln (Min Wage)		0.029		0.007		0.000
		(0.026)		(0.022)		(0.031)
ln (Capital)		0.018***		0.012***		0.010***
		(0.002)		(0.001)		(0.002)
ln (Output)		0.166***		0.136***		0.114***
		(0.002)		(0.001)		(0.002)
Constant	8.865***	5.867***	8.964***	6.327***	8.847***	6.733***
	(0.074)	(0.355)	(0.073)	(0.276)	(0.117)	(0.391)
r2	0.313	0.441	0.244	0.423	0.234	0.390
N	52,006	51,731	84,547	84,052	31,868	31,808

Notes: Standard errors are in parentheses. The sample consists of all treated and control firms for the years 2000-2002 and 2004-2006. All models include year, region, and industry effects.

Table 2.5: Difference in Differences Results for the Salary of Production Workers

	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.283***	-0.302***	0.112***	0.087***	0.120***	0.107***
	(0.007)	(0.010)	(0.006)	(0.006)	(0.008)	(0.008)
Post-2003	0.040***	0.008	0.079***	0.036***	0.307***	0.004
	(0.008)	(0.014)	(0.007)	(0.011)	(0.012)	(0.013)
Treated * Post-2003	0.061***	0.077***	0.094***	0.087***	0.073***	0.072***
	(0.010)	(0.009)	(0.008)	(0.008)	(0.011)	(0.011)
ln (Min Wage)		0.061**		0.023		0.030
		(0.026)		(0.022)		(0.031)
ln (Capital)		0.011***		0.004***		0.002
		(0.002)		(0.001)		(0.002)
ln (Output)		0.151***		0.117***		0.095***
		(0.002)		(0.001)		(0.002)
Constant	8.750***	5.577***	8.675***	6.509***	8.446***	6.806***
	(0.070)	(0.349)	(0.075)	(0.290)	(0.102)	(0.405)
r2	0.275	0.384	0.233	0.366	0.235	0.341
N	52,002	51,727	84,539	84,044	31,866	31,806

Notes: Standard errors are in parentheses. The sample consists of all treated and control firms for the years 2000-2002 and 2004-2006. All models include year, region, and industry effects.

Table 2.6: Difference in Differences Results for the Benefits of Production Workers

	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	1.216***	0.057**	0.290***	0.234***	0.272***	0.234***
	(0.018)	(0.025)	(0.017)	(0.015)	(0.022)	(0.019)
Post-2003	-0.354***	-0.308***	-0.275***	-0.159***	-0.119***	0.049
	(0.042)	(0.061)	(0.031)	(0.023)	(0.034)	(0.047)
Treated * Post-2003	-0.281***	-0.279***	0.079***	0.085***	0.058*	0.071**
	(0.029)	(0.027)	(0.024)	(0.022)	(0.033)	(0.030)
ln (Min Wage)		-0.040		-0.005		-0.047
		(0.070)		(0.055)		(0.076)
ln (Capital)		0.082***		0.078***		0.068***
		(0.005)		(0.004)		(0.005)
ln (Output)		0.252***		0.263***		0.235***
		(0.006)		(0.004)		(0.005)
Constant	6.588***	2.740***	7.612***	1.578**	6.664***	2.831***
	(0.198)	(0.936)	(0.219)	(0.729)	(0.395)	(1.050)
r2	0.313	0.392	0.187	0.377	0.141	0.325
N	34,310	34,115	55,682	55,309	21,488	21,436

Notes: Standard errors are in parentheses. The sample consists of all treated and control firms for the years 2000-2002 and 2004-2006. All models include year, region, and industry effects.

Table 2.7: Difference in Differences Results for the Capital/Labor Ratio

	By Firm Size		By Location		Matched Control	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.124***	-0.713***	0.023	0.000	-0.019	-0.020
	(0.024)	(0.032)	(0.020)	(0.020)	(0.026)	(0.026)
Post-2003	0.104***	-0.067**	0.160***	-0.039	0.104***	-0.193**
	(0.023)	(0.034)	(0.019)	(0.050)	(0.037)	(0.096)
Treated * Post-2003	0.231***	0.252***	0.107***	0.079***	0.116***	0.093***
	(0.032)	(0.031)	(0.025)	(0.026)	(0.035)	(0.035)
ln (Min Wage)		0.392***		0.370***		0.415***
		(0.086)		(0.070)		(0.108)
ln (Output)		0.229***		0.161***		0.091***
		(0.006)		(0.003)		(0.005)
Constant	8.611***	0.319	9.187***	1.690*	8.879***	1.735
	(0.294)	(1.162)	(0.247)	(0.912)	(0.370)	(1.391)
r2	0.100	0.134	0.095	0.129	0.092	0.103
N	52,006	51,731	84,547	84,052	31,868	31,808

Notes: Standard errors are in parentheses. The sample consists of all treated and control firms for the years 2000-2002 and 2004-2006. All models include year, region, and industry effects.

Table 2.8: Summary of Difference in Differences Results for Robustness Checks

	Pre Assignment		Diff Size Cutoffs		Near Capital	
	(1)	(2)	(3)	(4)	(5)	(6)
Output	0.054*	-0.043**	-0.155***	-0.078***	0.024	-0.013
	(0.029)	(0.021)	(0.025)	(0.019)	(0.031)	(0.017)
Job Prod	0.023	-0.006	-0.101***	-0.055***	0.009	-0.013
	(0.017)	(0.014)	(0.013)	(0.011)	(0.020)	(0.012)
Prod Wage	0.035***	0.020**	0.019*	0.039***	0.055***	0.051***
	(0.011)	(0.010)	(0.010)	(0.009)	(0.008)	(0.007)
Prod Salary	0.076***	0.065***	0.052***	0.070***	0.052***	0.049***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.007)
Prod Benefits	-0.213***	-0.272***	-0.277***	-0.258***	0.082***	0.105***
	(0.031)	(0.029)	(0.027)	(0.025)	(0.024)	(0.022)
Cap/Lab	0.402***	0.384***	0.215***	0.243***	0.125***	0.114***
	(0.035)	(0.034)	(0.027)	(0.026)	(0.026)	(0.026)

Notes: Standard errors are in parentheses. The sample consists of all treated and control firms for the years 2000-2002 and 2004-2006. Only the coefficient on the treatment effect is reported.

CHAPTER 3

POVERTY AND MONOPSONY: EVIDENCE FROM THE INDONESIAN LABOR MARKET

3.1 Introduction

Industrialization is often seen as an engine of growth that will help lift people out of poverty. The jobs that people are able to get in formal labor markets tend to have both higher and more stable wages than what they could earn in agriculture or the informal sector. As the industrial sector grows in an economy, people leave the agricultural sector to find jobs in manufacturing plants. Along with the new job, comes better pay which allows the worker to increase the standard of living for their household. This pattern has occurred in both Korea and Taiwan, and is happening in China and Indonesia.

Indonesia's GDP per capita has increased five-fold in the last 40 years, and its poverty rate has declined by over 40 percentage points in the last 25 years [1]. Some of this decline in poverty in Indonesia can be attributed to the growth of its manufacturing sector. In the last 25 years, the manufacturing sector has created over 14 million new jobs. The average yearly wage of a manufacturing worker in Indonesia is US$ 1,819, which alone is enough to support a family of three above the poverty line. With over 14 million new jobs, this roughly suggests that 43% of the poverty reduction in Indonesia over the last 25 years has been due to people getting jobs in the manufacturing sector. These numbers reflect amazing progress for Indonesia, however, could they have been even better?

[1]All figures referenced in this section are based on the author's calculations using data from the World Bank's World Development Indicators and from Indonesia's manufacturing census (SI). The poverty line used is US$1.25 converted at purchasing power parity rates.

That is, could Indonesia's process of industrialization have lifted even more people out of poverty? Industrialization might have had a bigger impact on poverty if the jobs paid higher wages or if the jobs were more geographically dispersed. This paper investigates the impact of another factor, the competitiveness of the labor market. Recent work has shown that 60% of the manufacturing firms in Indonesia are sourcing labor monopsonistically (Brummund, this volume). This implies firms are paying lower wages and hiring fewer workers than they would if they sourced labor competitively. This paper will quantify how many more people could have been lifted out of poverty in Indonesia if the labor markets were perfectly competitive.

Using firm-year level estimates for each firm's market power, this paper will calculate the implied deadweight loss for each firm. I will then estimate what the wage and employment levels would have been for each firm if they hired labor competitively. These estimates are then taken to household data where I calculate how many more people would have been able to work their way out of poverty through industrialization if the labor markets were not monopsonistic. This exercise has not been possible previously as the evidence for the monopsonistic behavior of firms was not granular enough to facilitate the link to household consumption.

The next section provides a brief literature review. Section three explains the empirical methods used for the analysis. Section four describes the data, and section five presents the results in three sub-sections, market power, deadweight loss, and poverty. Section six concludes and provides a brief policy discussion.

3.2 Literature

This research is connected to two main sets of literature. First, this paper examines a common theme in the development literature on the importance of industrialization in the development of an economy, and the associated reduction in poverty. The second literature discusses the link between competition policy and poverty.

There have been many papers discussing both the theoretical foundations for the role of industrialization in economic development, and also empirical evidence for the phenomenon. Rosenstein-Rodan (1943) discusses the role of industrialization in the context of a "big-push", where the development of the industrial sector creates its own demand for goods produced by the industrial sector as the newly employed workers have higher incomes with which they demand additional goods. Murphy, Shleifer and Vishny (1989) extend this idea by showing that multiple equilibria are possible, both a non-industrial economy and an industrialized economy, depending the parameter values.

Rostow (1960) more directly discusses the role of industrialization in the development of an economy, with each of his five stages being described in relationship to the nature of industrialization in the economy. The stages go from no industrialization, to advancement of a few industries, and then diversification and wide-spread growth. Its not too difficult to see examples of this pattern throughout history, starting with the Industrial Revolution in England, and more recently with Korea and China.

There have also been more formal analyses of the impact of industrialization on poverty. The 1990 World Development Report (WDR) focused on poverty and the progress that had occurred up till then at reducing poverty. The report describes how poverty alleviation has been achieved through two primary means, harnessing the most valuable asset of the poor, their labor, and also through the increased provision of basic social services to the poor. One of the background papers for the 1990 WDR examined more specifically how the wages for unskilled workers changed throughout industrialization (Polak and Williamson 1991). They find that real wages for unskilled workers grow more slowly initially, but then grow proportionately with the rest of the economy as industrialization progresses.

A recent study has found evidence for the “big push” proposed by Rosenstein-Rodan. Magruder (2011) examines changes in the minimum wage in Indonesia over the 1990’s. He finds that formal employment increases in response to higher minimum wages, along with demand for locally produced products, which supports the idea of a coordinated move from a non-industrialized equilibrium to an industrialized one.

The second literature that I build on is work dealing more directly with the link between competition and poverty. Rodriguez-Castelan (2011) examines the theoretical link between product market concentration and poverty. He finds conditions for which higher market concentration could both lower or raise the poverty index, though the conditions for higher market concentration leading to higher levels of poverty are more realistic.

Goto (2011) studies the optimal minimum wage for poverty reduction, and finds that the optimal minimum wage is only equal to the competitive wage in certain special cases. Typically, the optimal minimum wage is higher than the competitive wage. Two other papers have also studied the relationship between minimum wage and poverty, finding that the impacts of a minimum wage policy depends on the employment composition of the household (Fields and Kanbur 2007; Fields, Han and Kanbur 2007).

This paper builds on these literatures by providing, to my knowledge, the first empirical evidence for the relationship between competition policy and poverty. This paper also shows how industrialization could have had even larger impacts on poverty if the labor market was more competitive.

3.3 Empirical Approach

3.3.1 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[2] is given as:

$$E = \frac{R'(L) - W(L)}{W(L)}. \tag{3.1}$$

[2]This measure is analogous to the Lerner Index used to measure product market power.

It is easy to show that $E = \epsilon^{-1}$, where ϵ is the elasticity of the labor supply curve[3]. 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, 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. This paper follows the work of Brummund (this volume), where a technique for estimating MRPL was developed and tested. The general idea of the approach 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. Brummund (this volume) has shown that the trans-log form does not fit the Indonesian data well, so I focus on the Cobb-Douglas specification here. 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

[3] Let $\epsilon = \frac{WL'(W)}{L(W)}$. Substitute the first order condition for wages into the equation for E to get $E = \frac{W'(L)L}{W(L)} = \epsilon^{-1}$.

productivity[4]. β_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:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \epsilon_{it}, \tag{3.2}$$

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:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \omega_{it} + \nu_{it}, \tag{3.3}$$

with ω_{it} representing firm-specific productivity and ν_{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. Various authors (Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2006) have improved upon this method, though this strand of approaches 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 Blun-

[4]The 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.

dell 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 within 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.

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, and the Blundell-Bond method allows the inclusion of firm fixed effects whereas the Olley-Pakes approaches do not. 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.

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 β_L. To weaken the impact of this assumption, I estimate the production function separately by four-digit industries. 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

$$MRPL_{it} = \frac{\partial Y_{it}}{\partial L_{it}} = \frac{\hat{\beta}_{L_j} Y_{it}}{L_{it}}, \tag{3.4}$$

for firm i, year t, and industry j. It is then straightforward to calculate the firm-year specific measure of market power from equation (3.1).

3.3.2 Deadweight Loss

If firms are behaving monopsonistically, then there is a deadweight loss as a result of their production decisions. Firms are choosing levels of employment and wages and that are less than efficient to the economy as a whole. The size of this deadweight loss can be calculated using the measure of market power estimated in the previous section, and the observed production choices for each firm. The key step is to find what the efficient combination of employment and wages are for each firm (L^* and W^* respectively), and then compare those with the observed choices.

The firm's optimal combination of employment and wages is found at the intersection of the marginal revenue curve and the marginal cost curve. In the labor market, the marginal revenue curve is labor demand curve, and if the labor market is competitive, the marginal cost curve is the labor supply curve to the firm. If the labor market is not competitive, then the labor supply curve is not equal to the marginal cost curve, which leads the firm to choose a different optimal bundle (Point A on Figure 3.1). However, even if the labor supply curve to the firm is not competitive (i.e. not flat), it is still efficiency increasing for the firm to choose the point where the labor demand curve intersects the labor supply curve (Point B), instead of the marginal cost curve (Point A), as the firm can sell the output generated by the extra worker for more than what the firm would have to pay in wages. But it is not optimal from the firm's perspective to hire more than L workers if it is facing an upward sloping labor supply curve, because it would have to raise the wages of all the existing workers, and the total additional costs are greater than the additional revenue the firm can generate. Thus the deadweight loss is equal to the triangle ABC in the Figure 3.1.

To find the efficient combination of employment and wages (L^* and W^*), I first need to estimate the parameters of the labor supply and labor demand curves. The labor demand curve shows the marginal revenue product of labor for each level of employment at a particular firm. This curve is estimated by separately regressing the marginal revenue product of labor on employment for each firm. There is an observation for each year that a firm is in the data set, providing the sample for each regression. This approach yields one labor demand curve for each firm, which implies that a firm's technology does not change over time. While this is a restrictive assumption, the alternative is to assume that all of the firms in a particular industry share the same technology, which could vary over time. I think the differences in productivity across firms are greater than the differences in productivity within a firm over time, implying that the assumption of a firms technology not changing over time is more accurate.

The measure of market power, E, is used to determine the labor supply curve for each firm. And since the measure of market power is captured for each firm in each year, there is a distinct labor supply curve for each firm in each year. This implies that a firm's efficient choice of employment and wage changes from year to year based on changes in the local labor market, not due to changes in the firm's productivity.

The firm specific measure of market power can be expressed as an elasticity, and using the observed levels of employment and wages, the slope of the labor supply curve, β_1, can be determined as follows:

$$\begin{aligned}
E &= \frac{\partial W}{\partial L}\frac{L}{W} \\
\frac{MRPL - W}{W} &= \frac{\partial W}{\partial L}\frac{L}{W} \\
\frac{MRPL - W}{L} &= \frac{\partial W}{\partial L} = \beta_1 \\
\beta_1 &= \frac{MRPL - W}{L}. \qquad (3.5)
\end{aligned}$$

The y-intercept of the labor supply curve, β_0, can then be determined:

$$\begin{aligned}
\beta_0 &= W - \beta_1 L \\
\beta_0 &= W - \frac{MRPL - W}{L} * L \\
\beta_0 &= 2W - MRPL. \qquad (3.6)
\end{aligned}$$

Letting the labor demand curve be represented as, $W(L) = \alpha_0 + \alpha_1 L$, the intersection of the two curves yields the efficient choices of employment and wages can be found according to:

$$W^* = \frac{\beta_1 * \alpha_0 - \alpha_1 * \beta_0}{\beta_1 - \alpha_1} \qquad (3.7)$$

$$L^* = \frac{W^* - \beta_0}{\beta_1}. \qquad (3.8)$$

The deadweight loss is then calculated for each firm with market power as $DWL = (1/2)(MRPL - W)(L^* - L)$, where $MRPL$ is the value of the labor demand curve at the actual employment level L.

3.3.3 Poverty

If firms are behaving monopsonistically in the labor market, then both L^* and W^* would be greater than the observed levels of employment and wages. This implies that if labor markets operated competitively, more workers would be employed in the manufacturing sector in Indonesia, and all workers for monopsonistic firms would have higher wages. These changes imply that more people would be above the poverty line, and this section describes how to quantify exactly how many.

Market power is measured at the firm level, but poverty is determined at the individual level. Without knowing exactly who works for what firm, I pass the changes in wages and employment to the individual worker through their local labor market. This assumption states that if a labor market operated competitively, the workers in that labor market would be the most impacted. Since market power is determined by both market and firm specific factors (Manning 2003, Brummund, this volume), it would be preferable to connect workers to specific firms, but that is not possible with the data used in this analysis. I define the local labor market as the local geographic district (kabupaten), which is similar to a county in the United States. This implies that a manufacturing worker in a district could work for any other manufacturing firm in the same district, but would not be able to move to a different district.

To carry over the implied changes in wages and employment to individuals, I calculate the median change for each district in each year in the firm data. For wages, I apply the median change in wages to each manufacturing worker and their household in that district in that year. However, poverty is commonly measured in developing countries based on each person's level of consumption, as there is often a lot of non-market production that contributes to the household standard of living which is not captured in their measured income. To carry over the increase in wages, I assume that if wages increased by

25%, than consumption also increased by 25%. For example, if the median firm with market power in district X in year Y would have paid 25% higher wages if it hired labor competitively that year, I increased the per capita consumption every manufacturing workers' household in district X in year Y by 25%.

It is a little more complicated to carry over the implied changes in employment, as I need to determine who gets hired. I pick people not currently employed in manufacturing, but who look most like those employed in manufacturing. I use standard propensity score methods to determine who has the highest probability to be employed in manufacturing. I run a probit over the whole sample with an indicator for whether the person is employed in the manufacturing sector as the dependent variable. As independent variables, I use information about the person themselves, their spouse, their household, as well as province dummies. For the person, I use their age, sex, education, an indicator for whether their spouse is present, an indicator for whether they are employed, and an indicator for self-employment. I use their spouse's level of education, an indicator for whether the spouse is employed, and an indicator if the spouse is employed in manufacturing. For individuals that do not have a spouse, these spouse variables are set to 0. The spouse variables are then interactions with the spouse-present variable. This formulation allows all of the observations to be included, yet still conditioning on information about the spouses. I also use information about the other members of the household. I use an indicator if other members (besides themselves and their spouse) are present, controls for the average years of education for the other members, the total number of people employed, and the total number of people employed in manufacturing. Each of these values excludes the respondent and the spouse (if present) in their construction. The household variables are also set to 0 if no other members of the household are present. After estimating, I predict each person's probability of being employed in the manufacturing sector. I then select the people with the highest propensity scores, who are not currently employed in manufacturing, and who consume less than the average manufacturing worker in their district, to be added to the manufacturing sector. This selection is done separately by district.

For example, if there were 100 people employed in district X in year Y, and employment would have increased by 30% if that labor market operated competitively, I pull the 30 people with the highest propensity scores into the manufacturing sector in that district. Since being employed in the manufacturing sector is usually the household's primary income source, I first give each household member the average current consumption of all manufacturing workers in their district, and then the average competitive consumption. I apply these changes in steps in order to separate out the wage and employment impacts of making the labor markets competitive.

I calculate poverty at the individual level, based on household consumption. I then compare the per capita consumption to the US $1.25 per day poverty line using Purchasing Power Parity exchange rates. I calculate both the poverty headcount ratio and the poverty gap indices. Both measures can be represented using the Foster, Greer, and Thorbecke (1984) class of poverty measures, P_α, defined as:

$$P_\alpha = \frac{1}{N} \sum_{i=1}^{H} \left(\frac{z - y_i}{z} \right)^\alpha , \tag{3.9}$$

where N is the number of observations, H is the number of poor people, z is the poverty line, y_i is person i's income, and α is the sensitivity parameter. The headcount ratio is P_0 and the poverty gap is P_1, which takes into account how far people are below the poverty line.

I then calculate each poverty measure four times. The first is the actual poverty measure. The second is the poverty measure after the wages of existing manufacturing workers have been increased. Third, the poverty measure is calculated after some people have been pulled into manufacturing employment from unemployment, but no wages have been increased. Finally, the poverty measure is calculated after both wages and employment increased. These measures are calculated separately to identify how much of the overall change in poverty is due to the increase in wages, or due to the increase in the number of people employed in the manufacturing sector.

I also use four different poverty lines. The lowest poverty line is the national poverty line. The next is the more internationally comparable line of $1.25/day, which I convert to Rupiah using Purchasing Power Parity (PPP) exchange rates. The third poverty line I use is the $2.00/day, also converted via PPP. The last, and highest, poverty line is the $1.25/day poverty line, but converted to Rupiah using the real exchange rate. Each of the poverty lines provides information about a slightly different part of the income distribution.

To help understand the relative role of monopsony in determining the level of poverty in Indonesia, I perform a simple Oaxaca-Blinder (OB) decomposition. This technique breaks down a difference in outcomes between two groups into what can be explained by differences in levels of observed factors, and what can be explained by differences in returns to those factors. A common application of this technique is to break down the wage gap between males and females. Here, I use poverty as the outcome variable, and the two different time periods as the two groups. Therefore, the Oaxaca-Blinder decomposition is able to identify how much of the change in poverty between the two periods is due to changes in observable characteristics, and how much is due to changes in the returns to those characteristics.

The OB decomposition technique starts with the mean poverty rates in the two different periods, $\bar{P}_A$ and $\bar{P}_B$. Letting the poverty rate be determined by some set of observable characteristics, X_t for years $t = A, B$, then $P_t = \beta_t' X_t + \epsilon_t$. Evaluating this equation at the means for each time period, and taking the difference yields,

$$\bar{P}_A - \bar{P}_B = \beta_A' \bar{X}_A - \beta_B' \bar{X}_B.$$

Then add and subtract the counterfactual term $\beta_A' \bar{X}_B$, and rearrange terms to get,

$$\bar{P}_A - \bar{P}_B = \beta_A'(\bar{X}_A - \bar{X}_B) - (\beta_B - \beta_A)' \bar{X}_B. \tag{3.10}$$

The first term on the right side of the equation represents the change in poverty due to changes in the observable characteristics between the two periods. The second term captures the change in poverty due to changes in the returns to the observable characteristics. This exposition used $\beta_A' \bar{X}_B$ as the counterfactual, which implies that β_A is the true set of returns to characteristics. However, any set of β's could be used to construct the decomposition. In the analysis below, I use the β's from a pooled regression that includes all of the years in the sample.

3.4 Data

The data used to calculate market power come from Indonesia's 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 calculate the impact of market power on poverty, I make use of data from Indonesia's Family Life Survey (IFLS). The IFLS data is a privately collected longitudinal survey in Indonesia, containing detailed information on individuals, households, and communities. The sample is representative of about 83% of the Indonesian population in 1993 and contains over 30,000 individuals living in 13 of the 27 provinces in the country. I use data from years 1993 and 2007, the first and fourth waves of the IFLS survey. The data is a panel, though I do not make use of that structure for this analysis.

Using the SI data, I constructed an average wage measure for each firm by adding total wages to total benefits, and then dividing 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 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.

Summary statistics for the SI data can be found in Table 3.1. 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.

Summary statistics for the IFLS data can be found in Table 3.2. The first two columns show statistics for 1993 and the last two columns show summary statistics for 2007. In 1993, there were 5.48 people in each household. The average age was 26.3, and 50% of the people in the sample are female. The average person has not completed primary school, and under 30% of the sample has a job. The average monthly per capita consumption is just under 60,000 Rupiah, which is approximately US$ 94. About 51% of the workforce is self-employed. The sector with the largest share of workers is agriculture, followed by manufacturing, wholesale, and then the public service sector. The other sectors that are not displayed are mining, electricity, construction, transportation, finance, and other.

In 2007, the household size increased, the average person is older, has more education, more likely to be employed, but less likely to be self-employed, and has a much higher per capita consumption. It is important to note that the IFLS is a panel dataset, so the increase in average age and education are to be expected. The average age only increases by 5 years over the 15 year period because splits in households were followed, and new household members added to the survey.

3.5 Results

3.5.1 Market Power

The first set of results summarize the monopsonistic behavior of manufacturing firms in the labor market[5]. Table 3.3 shows Pigou's E for both production and non-production workers. The median value of market power for production workers is 1.93, which suggests that the median firm has significant amounts of market power over production workers. If the firm operated competitively, Pigou's E would be equal to zero, as the marginal revenue product of labor would equal the wage paid. The last three columns of Table 3.3 categorize the distribution of market power by displaying the percentage of observations that lie in three ranges of market power. Column (4) shows the percentage of firms with values of Pigou's E below 0.33, which implies that firms have little to no market power. 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. 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

[5]These results match those found in Brummund (this volume), and more details about the estimation and tests of the results can be found in that paper.

power

While the bottom half of the table shows results for non-production workers, these results are suspect, because this approach for measuring market power assumes that all of the workers within each category have the same level of productivity. This is a restrictive assumption, but may be appropriate for low-skilled manufacturing workers of the type considered in this data. However, this assumption definitely does not hold for non-production workers, whose category includes both management and administrative staff. 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.

3.5.2 Deadweight Loss

Using these measures of market power for each firm and year, the next step in the analysis is to determine the size of the deadweight loss implied by their monopsonistic behavior. While this value is informative, the more practical values are the predicted changes in employment and wages, ΔL and ΔW. In order to find those values, the parameters of the labor demand and labor supply curves must be estimated.

The labor demand curve is estimated by separately regressing the marginal product of labor on the level of employment for each firm. This regression was run 33,290 times, once for each firm in the data. The summary of the results of these regressions are shown in the top half of Table 3.4. The average curve is downward sloping, as theory would predict, though there is considerable variation. The median curve is also downward sloping. 86.4% of the slope coefficients are statistically significant. The bottom half of Table 3.4 summarizes each firm's labor supply curve. These parameters are calculated from each firm's market power measurement, and their observed levels of wages and employment. Both the mean and median curves are upward sloping, which is consistent with basic economic theory.

Using these parameters for the labor supply and labor demand curves, the levels of employment and wages that would prevail if the firms operated competitively in the labor market can be calculated. These competitive outcomes, as well as the associated changes in each value are displayed in Table 3.5. I drop any observations that did not have statistically significant estimates for the labor demand curve, and recode any values for the change in wages and change in labor that predicted a decrease in wages or employment to be zero. The top half of the table displays summary statistics for the current wage, the estimated competitive wage, and the associated percentage change in wages. The median percentage change in wages is 72%, which says that the median worker's wages would increase by 72% if the manufacturing firms behaved competitively in the labor market. The bottom half of the table presents results for employment. The median worker works for a firm that would would hire 38% more workers if the firm operated competitively. The percentage change for both wages and employment are high, and suggest that manufacturing firms in Indonesia are hiring too little cheap labor.

Table 3.6 presents the percentage change in wages and employment separately for each major industry in the SI data. Looking at the median values for the change in wages, the industries with the largest changes are Communication, Publishing, Tobacco, Chemicals, and Apparel. The industries with the smallest changes in wages are Minerals, Transportation, Leather, and Furniture. Looking at the median values for the change in employment, the values are much more closely bunched. The industries with the highest values are Publishing, Apparel, Communication, and Chemicals, which matches the industries with the largest changes in wages. For the most part, the industries with the smallest changes in wages also had small changes in employment, Minerals, Machinery, Transportation, Leather, and Tobacco.

The last step in this section is to carry over these predicted changes in wages and employment to the individual level data, IFLS. I do that by aggregating up the percentage changes in wages and employment to the district (kabupaten) for each year. I take the median value weighted by the number of production workers after restricting the sample a few ways. I ensure that all of observations come from industries that produced valid estimates of the productions function.

3.5.3 Poverty

The previous section showed that if the firms in the manufacturing sector operated competitively, there would be significant increases in both wages and employment. This section examines how those predicted changes impact the poverty rate in Indonesia. However, the manufacturing sector only comprised 7% in 1993 and 15% in 2007 of total employment, so we may not expect a very large change in the overall poverty rate. As mentioned above, I calculate both the poverty headcount ratio (P_0) and the poverty gap (P_1) using four different poverty lines.

The IFLS has broad coverage, but is not nationally representative. Therefore, I first compare the poverty headcount ratios I calculated in the IFLS to national poverty rates. These results are presented in Table 3.7. The first three columns show results using the World Bank's World Development Indicators, and the last three columns show the results using the IFLS data. Overall, the IFLS broadly supports the World Bank data, though there is a larger reduction in poverty in the IFLS data. This could just be a statistical anomaly due to the relatively small sample size, or because the regions the IFLS chose to sample from had a greater fall in poverty than did the other regions.

Table 3.8 then displays the actual poverty headcount ratio, and three alternative poverty rates in 1993. The first alternative is shown in column (2), and shows what the poverty rate would be if the existing manufacturing workers were paid a competitive wage. Column (3) displays what the poverty rate would be if there was a competitive level of employment, all who were paid at the existing rate. The last column combines both the competitive wage and the competitive level of employment. The top panel shows the poverty headcount ratio using four different poverty lines, and the bottom panel shows the poverty gap.

While all of the poverty lines are informative, I will focus the discussion on the \$1.25/day (PPP) poverty line, as that is the most internationally comparable figure. In 1993, the poverty rate was 65%. If manufacturing workers were paid competitively, the poverty rate would have been 57%, a 8 percentage point reduction. If manufacturing firms hired up to the competitive level of employment, but paid them the current wage, the poverty rate would have been 60%, a significant reduction, but not as large as the reduction associated with the increase in wages. If both changes are applied, the competitive wage and level of employment, the poverty would have been 50% in 1993, a 15 percentage point reduction. This is a large effect, especially considering the manufacturing sector is a small portion of the overall workforce.

The bottom half of Table 3.8 shows the results for the poverty gap measure in 1993. The actual measure is 0.285, and would decrease to 0.251 if the labor market was competitive. This is a smaller absolute change than the change for the headcount ratio. Changing to the competitive level of employment has a similar impact on the poverty gap as does the change to the competitive wage. This is different from the impact on the headcount ratio, though the difference makes sense. People already employed in the manufacturing sector have a relatively good standard of living, so those poor are probably close to the poverty line, and increasing their wages will decrease the headcount ratio more so than the poverty gap measure. However, pulling people into the manufacturing sector will have a larger impact on the lower end of the distribution, which is what is seen in Table 3.8.

Table 3.9 shows the results for poverty in 2007. The actual poverty headcount ratio fell from 65% in 1993 to 16.4% in 2007. This is a large change, and shows the progress in poverty reduction that Indonesia has made over this 15 year period. The impact of a competitive labor market in 2007 is smaller, though this can partly be attributed to the smaller base poverty rate. If the labor market was competitive, the poverty headcount ratio would have been 15.1%, about a 1.3 percentage point reduction in poverty. Columns 2 and 3 show that the competitive level of employment has a larger impact on poverty than does the competitive wage. This result is the reverse what the relative size of the effects in 1993. It is not surprising that the relative magnitudes changed, since there was such a large change in poverty over this time period, the characteristics of the poor in 2007 are surely different from 1993.

The results in this section show that monopsonistic behavior by manufacturing firms in the labor market has been a drag on the poverty reduction progress of Indonesia over the years 1993 to 2007. If the manufacturing firms operated competitively in the labor market, the overall poverty rate would have been 15 percentage points lower in 1993, and would have decreased to a rate 1.3 percentage points lower in 2007 than did the actual poverty rate. The two different facets of the change, competitive wages and competitive levels of employment, had similarly sized impacts on poverty reduction.

3.6 Conclusion

This paper has investigated the impact of the monopsonistic behavior of manufacturing firms in Indonesia on poverty. It first identified the amount of market power each firm had by estimating each firm's marginal revenue product of labor and comparing it to the wages each firm paid. The median value of market power was 1.93, with about 60% of the firms having significant amounts of market power. I then calculated labor supply and labor demand curves for each firm enabling the calculation of the optimal level of employment and wages. If manufacturing firms hired labor competitively, the wages of their workers would have increased by 72% and they would have hired 38% more workers.

The next step was to take these relative changes in wages and labor to the IFLS dataset to enable the poverty analysis. Using the US $1.25/day poverty line and Purchasing Power Parity exchange rates, the actual poverty rate in

Indonesia started at 65% in 1993 and decreased to 16% in 2007. However, if the manufacturing firms behaved competitively, the poverty rate would have started at 50% in 1990, and decreased to 15%. These results show that the monopsonistic behavior of firms was a drag on poverty reduction progress in Indonesia, though less of a drag in 2007 than it was in 1993.

Changing to competitive labor markets could influence poverty through two channels, by increasing wages or by increasing the level of employment. The results show that each channel had a significant impact on poverty reduction, and had similar magnitudes.

This research has several policy implications. The primary implication is about the importance of competitive labor markets in helping reduce poverty within a country. A labor market could be made more competitive in many ways. One way would be to reduce the moving costs associated with workers finding new jobs. This could be a reduction in the real physical moving costs, or an increase in the information about other jobs, making it easier for workers to learn about other opportunities. An increase in the number of employers would also make the labor market more competitive, as the firms have to compete for workers. The labor market could also become more competitive if the working conditions at each firm were made more similar. This would reduce the difference in preferences workers have for firms, and flatten the labor supply curve to each firm.

Another main implication of this research is about the relevance of a minimum wage in Indonesia. A minimum wage policy can increase efficiency in a monopsonistic labor market, however each firm in this analysis has a different optimal wage level, so a minimum wage policy might be too blunt of a policy tool. Another policy implication is about the types of labor market policies that have the greatest impact on poverty. While this paper considered changes in wages and employment as a result of the elimination of monopsonistic behavior, there could be a multitude of other mechanisms to generate similar changes. This paper has shown that both channels have a similar sized impact on poverty reduction, though attention should be given as to where the targets of the policy currently are in the income distribution as compared to the poverty line. The relative impacts of the two channels would differ if the average manufacturing wage is not enough to support a household above the poverty line or if the average new manufacturing worker had a much lower previous level of income.

There are also related topics that would be interesting to pursue further. While this paper focused on poverty, market power might also influence inequality. Inequality would capture changes to the whole distribution of incomes, and not just those around the poverty line as done in this paper. It would also be interesting to compare the the size of the deadweight loss found in Indonesia to that of a different country.

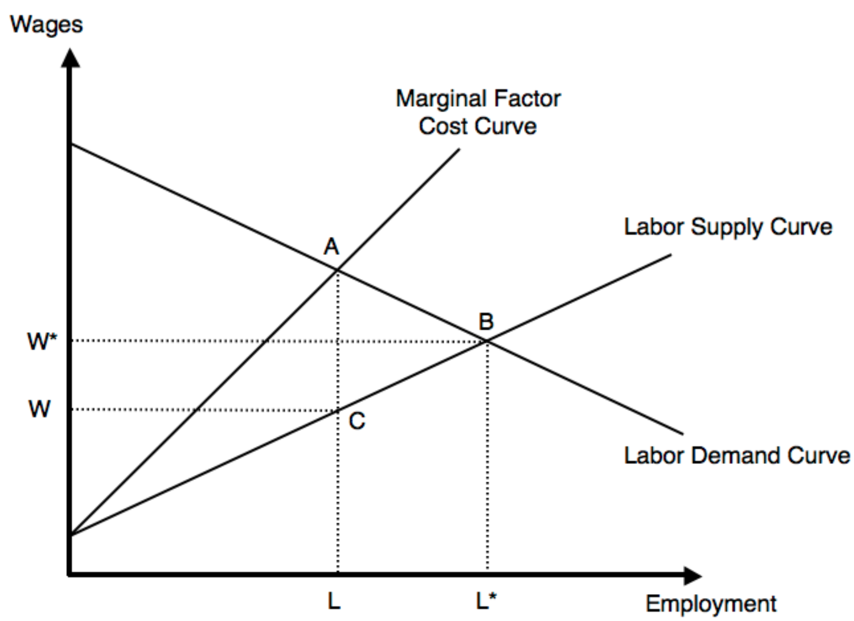

Figure 3.1: Labor Market Diagram with an Increasing Labor Supply Curve

Table 3.1: Summary Statistics of All Indonesian Manufacturing Establishments Using the SI Data

	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 3.2: Summary Statistics of the IFLS Data

	1993		2007	
	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
Household Size	5.48	2.26	6.32	3.06
Age	26.28	18.85	31.13	21.02
Female	0.50	0.50	0.50	0.50
Education	4.23	3.83	8.60	4.22
Employed	0.28	0.45	0.34	0.47
Consumption	57,850	73,491	503,915	483,513
Self-Employed	0.51	0.50	0.39	0.49
Manufacturing	0.07	0.25	0.15	0.35
Agriculture	0.14	0.34	0.35	0.48
Wholesale	0.05	0.23	0.22	0.41
Public	0.02	0.15	0.19	0.39
Num	33,081		50,526	

Notes: All monetary values are nominal. Consumption is monthly per capita consumption expenditure.

Table 3.3: Summary of Pigou's Measure of Market Power, E

				Percent of firms with		
	Num	Mean	Median	$E < 0.33$	$0.33 \leq E \leq 2$	$E > 2$
	(1)	(2)	(3)	(4)	(5)	(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 is from the SI and covers years 1988 - 2006. Means are weighted by the number of employees of each type in each firm. Standard errors are in parentheses.

Table 3.4: Summary of Estimated Labor Supply and Labor Demand Curves

	Num (1)	Mean (2)	Std. Dev. (3)	Median (4)
Demand - Intercept	223,668	21,593.5	242,608.8	7,558.9
Demand - Slope	223,668	-111.52	7,826.8	-11.71
Supply - Intercept	226,209	-9,112.40	91,443.6	656.3
Supply - Slope	226,209	259.7	2,199.9	32.9

Notes: Data is from the SI and covers years 1998 - 2006. All values are in constant 2000 Rupiah, and are weighted by the number of production employees in each firm.

Table 3.5: Summary of Competitive Wage and Employment Levels

	Num (1)	Mean (2)	25th (3)	50th (4)	75th (5)
Current Wage	226,209	5,505.4	3,273.9	4,887.2	6,938.8
Competitive Wage	223,668	18,247.6	3,063.4	8,611.9	25,882.1
% Change W	223,668	9.58	0.00	0.72	3.64
Current Employment	226,209	1,718.0	168.0	550.0	1,352.0
Competitive Employment	223,668	2,278.5	89.2	572.3	2,016.0
% Change L	223,668	2.09	0.00	0.38	0.92

Notes: Data is from the SI and covers years 1998 - 2006. All values are in constant 2000 Rupiah and are weighted by the number of production employees in each firm.

Table 3.6: Summary of Changes in Wage and Employment by Industry

Industry	Wages 25th (1)	Wages 50th (2)	Wages 75th (3)	Employment 25th (4)	Employment 50th (5)	Employment 75th (6)
Food & Beverage	0.00	0.34	2.76	0.00	0.33	0.77
Tobacco	0.04	2.23	6.18	0.00	0.29	0.53
Textiles	0.00	0.87	3.37	0.00	0.37	0.88
Apparel	0.00	1.72	5.56	0.00	0.52	1.17
Leather	0.00	0.16	1.28	0.00	0.27	0.82
Wood	0.03	1.34	3.92	0.14	0.53	1.06
Paper	0.04	1.23	4.24	0.11	0.47	1.06
Publishing	0.65	2.99	7.55	0.21	0.66	1.35
Chemicals	0.03	1.49	8.83	0.04	0.47	1.03
Plastics	0.00	0.54	2.42	0.00	0.42	0.98
Minerals	0.00	0.02	0.42	0.00	0.23	0.83
Metals	0.17	0.96	2.51	0.22	0.46	0.74
Fabricated Metals	0.00	0.45	2.59	0.00	0.35	0.86
Machinery	0.00	0.35	2.81	0.03	0.34	0.71
Electrical	0.00	0.14	1.98	0.00	0.18	0.74
Communication	0.00	2.37	12.86	0.00	0.49	1.23
Vehicles	0.00	0.07	1.22	0.00	0.28	0.81
Transport	0.00	0.08	0.45	0.00	0.22	0.41
Furniture	0.00	0.29	1.53	0.00	0.34	0.83

Notes: Data is from the SI and covers years 1998 - 2006. All values are in percentages and are weighted by the number of production employees in each firm.

Table 3.7: Comparing Poverty Rates in IFLS to National Poverty Figures

Poverty Line	World Development Indicators 1993 (1)	World Development Indicators 2007 (2)	Diff (3)	IFLS Data 1993 (4)	IFLS Data 2007 (5)	Diff (6)
\$1.25/day	0.54	0.24	0.30	0.65	0.16	0.48
\$2.00/day	0.85	0.56	0.29	0.83	0.39	0.44
National	0.18	0.17	0.01	0.18	0.13	0.04

Notes: All IFLS calculations use sampling weights. [1] The WDI poverty rate using the National poverty line was not available in 1993. The closest available year is 1996, which is the number shown.

Table 3.8: Summary of Poverty Rates in 1993, Using Multiple Poverty Lines

	Actual (1)	Comp. Wage (2)	Comp. Employment (3)	Both Comp. (4)
Poverty Headcount Ratio				
National	0.177	0.153	0.152	0.134
$1.25/day (PPP)	0.648	0.567	0.595	0.497
$2.00/day (PPP)	0.828	0.749	0.806	0.673
$1.25/day (real)	0.817	0.738	0.796	0.663
Poverty Gap				
National	0.052	0.045	0.046	0.041
$1.25/day (PPP)	0.285	0.251	0.251	0.218
$2.00/day (PPP)	0.460	0.408	0.427	0.361
$1.25/day (real)	0.448	0.397	0.415	0.350

Notes: Data is from IFLS. All figures use sampling weights.

Table 3.9: Summary of Poverty Rates in 2007, Using Multiple Poverty Lines

	Actual (1)	Comp. Wage (2)	Comp. Employment (3)	Both Comp. (4)
Poverty Headcount Ratio				
National	0.134	0.127	0.127	0.124
$1.25/day (PPP)	0.164	0.157	0.155	0.151
$2.00/day (PPP)	0.387	0.365	0.360	0.348
$1.25/day (real)	0.490	0.459	0.462	0.438
Poverty Gap				
National	0.075	0.073	0.073	0.072
$1.25/day (PPP)	0.083	0.081	0.080	0.080
$2.00/day (PPP)	0.156	0.149	0.147	0.144
$1.25/day (real)	0.204	0.193	0.192	0.186

Notes: Data is from IFLS. All figures use sampling weights.

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