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

Peter Brummund*

University of Alabama

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Abstract Recent theoretical work has shown firms have market power when hiring workers that is independent of the labor market. However, current techniques for measuring market power are unable to separate the firm determinants of market power from the market determinants. This paper proposes a new method for measuring monopsony that yields a firm-specific measurement, which I apply to the Indonesian manufacturing sector. I find over half of establishments have significant amounts of market power, and show that individual establishment characteristics explain more of the variation in monopsony than the characteristics of the labor market in which the establishment participates in.

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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 the investigation of the relative importance of firm and market-level characteristics in determining market power.

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

A standard empirical measure of monopsony[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. The literature has used two main approaches for measuring monopsony, a static and dynamic approach. The static approach relies on instruments to move either the wages or employment level of a

[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.

[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.

firm independently of the other, and has found mixed support for monopsony (Sullivan 1989; Boal 1995; Falch 2010; Staiger, Spetz, and Phibbs 2010; Matsudaira 2013). The dynamic approach is based on estimating the recruitment and separation elasticities for a firm, and papers using this approach have found more consistent support for monopsony, with estimates for the elasticity of the labor supply curve between 1.5 and 3.7 (Hirsch, Schank, and Schnabel 2010; Ransom and Sims 2010; Ransom and Oaxaca 2010). With one exception, the existing evidence on monopsony is at an aggregate level. Ransom and Oaxaca (2010) estimate the market power of a specific firm, as all of their data comes from one grocery store chain[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, 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; Udry 1996; Barrett et al 2008).

I build on these literatures by leveraging the rich literature that has emerged on how to

[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.

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.

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[6].

The findings of this paper 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

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

[6]Hirsch and Schumacher (2005) also investigate whether market power was determined more at the firm or market level. 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.

of people out of poverty. Indeed, Indonesia's industrial sector has added approximately 15 million new jobs over the last 30 years[7]. However, the findings in this paper suggest that firms are behaving monopsonistically, which implies that fewer workers are employed and at lower wages than would be if firms were operating in competitive labor markets.

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

The next section develops the empirical methods that will be used for the analysis.

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

Section 3 then describes the Indonesian context and the data set. Section 4 presents the results on how prevalent monopsonistic behavior is among firms. Section 5 provides checks on my measure of monopsony and considers alternative explanations. Section 6 than analyzes the relative importance of firm specific and market characteristics in determining the market power of firms. Section 7 provides some robustness checks and section 9 then discusses policy implications and concludes.

2 Empirical Approach

2.1 Constructing the Measure of Market Power

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

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

It is easy to show that $E = \epsilon^{-1}$, where 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.

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

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 use both forms in the empirical work below, but 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 to logs and estimate the equation:

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

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

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

[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 simplicity.

with ω_{it} representing firm-specific productivity and ν_{it} capturing any measurement error or optimization errors on the part of the firm. There are two standard ways to estimate this model in the literature. The first method is more structural, and is based on the timing of the input decisions, allowing productivity to evolve according to a first-order Markov process between each decision point (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2006). 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 the other 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.

Both Ackerberg, Caves, and Frazer (2006) and Van Biesebrock (2007) provide useful comparisons of the two sets of approaches for estimating production functions. 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 large differences in the unobserved qualities of firms, which suggests that firm fixed effects are important. Firm effects can be included in the Blundell-Bond approach, but not the Olley-Pakes based methods. 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-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

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

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:

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

where $\hat{\Xi}$ is the efficient weighting matrix, which is the asymptotic variance of the first stage estimates, $avar(\hat{\pi})$. Then, to obtain the asymptotic variance of the estimates, I take the

Jacobian of $h()$ and represent it as $\hat{H}$, and then we have:

$$\begin{aligned} AsyVar(\hat{\theta}) &= \frac{1}{n}[\hat{H}'\Xi^{-1}\hat{H}]^{-1} && (6) \\ &= (\hat{H}'[avar(\hat{\pi})]^{-1}\hat{H})^{-1}. && (7) \end{aligned}$$

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

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

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 using higher level industry grouping, the two-digit industry code. 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. I present the results using the trans-log form in the robustness section.

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

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

firm as

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

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

2.2 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 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 assumes the skills of workers are able to crossover to other 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 power 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 the data has information on both wages and benefits paid to workers. However, there may be other non-pecuniary factors that influence 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.

2.3 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

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

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.

3 Data

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

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

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

Summary statistics for the data can be found in Table 1. Each observation is a firm-year. Firms are on average 14.5 years old, which is different from the average number of years of data I have for each firm, 12.4. Firms have on average 192 employees, with about 84% of them working as production workers (as opposed to non-production, or white-collar workers). Production workers make on average 4,261,000 rupiah/year, which is about US$506 (in year 2000 dollars). The non-production workers earn over twice as much.

4 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,

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

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

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

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

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

Taking all of these specification tests into account, the continued analysis will focus on firms in industries that pass all of the specification tests. From the original 306,217 firm-year observations, 241,093 passed all of the specification tests (78.7%). Table 3 compares the means of the firms that passed all of the specification tests to the firms in industries that did not pass at least one test.

The first two columns of Table 3 report the means and standard deviations for the firms in industries that passed all of the specification tests. Columns (3) and (4) display the means and standard deviations for the excluded sample. The last column displays the t-test for equality of means between the two samples. There are quite 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,

$$\frac{\partial Y}{\partial L_{PR}} = \frac{\hat{\beta}_{L_{PR}}Y}{L_{PR}} \tag{11}$$

$$\frac{\partial Y}{\partial L_{NP}} = \frac{\hat{\beta}_{L_{NP}}Y}{L_{NP}} \tag{12}$$

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

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

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

Comparing the top and bottom panels shows that there are more firms with a lot of market power over non-production workers than firms with market power over production workers. This suggests that non-production workers are less mobile and not as able to find alternative jobs, while the production workers are more mobile. This could be due to non-production jobs requiring more firm specific human capital, preventing non-production workers from having a lot of alternative jobs they could switch to. However, these results are suspect because there is a wide variety of worker quality within the non-production category, and my method assumes that all workers in each category have the same productive ability. For this reason, and because the production workers comprise the vast majority of the workforce, I will focus the rest of the analysis on the production workers.

5 Testing the Measure of Market Power

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

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

The last two columns check whether market power is positively correlated with market concentration. I allow market concentration to affect market power non-linearly, creating dummy variables for firms in markets with low and high levels of market concentration. I

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

define low and high as the firms in the lowest and highest quartiles of market concentration. The firms with medium levels of concentration are the omitted category. The results do show that firms in labor markets with low levels of concentration have less market power. The coefficient on the highly concentrated labor markets is positive, as theory would predict, 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.

6 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

$$e_{ijt} = \alpha_0 + \mathbf{X_{it}}\boldsymbol{\alpha_1} + \mathbf{Y_{jt}}\boldsymbol{\alpha_2} + \gamma_j + \nu_i + \epsilon_{ijt}, \tag{13}$$

[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.

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

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

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 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.

7 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.

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 7. 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 7. 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 7 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 7. 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 7. The results show significantly more market power for most firms, as evidenced by the median level of market power being 15 and over 82% of the firms having a lot of market power.

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

8 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[15]. 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 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

[15] 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).

what I found in Table **??**. 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.

References

Ackerberg, Daniel, Kevin Caves, and Garth Frazer. 2006. "Structural Identification of Production Fucntions," mimeo.

Alatas, Vivi, and Lisa A. Cameron. 2009. "The Impact of Minimum Wages on Employment in a Low-Income Country: A Quasi-Natural Experiment in Indonesia," *Industrial and Labor Relations Review*, Vol. 61, No. 2.

Anderson, T.W. and Cheng Hsiao. 1982. "Formulation and estimation of dynamic models using panel data," *Journal of Econometrics*, Vol 18: 47-82.

Arellano, Manuel and Stephen Bond. 1991. "Some Test of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, Vol. 58: 277-97.

Barrett, Christopher B., Shane M. Sherlund, and Akinwumi A. Adesina. 2008. "Shadow wages, allocative inefficiency, and labor supply in smallholder agriculture," *Agricultural Economics*, Vol. 38: 21-34.

Basu, Arnab K., Chau, Nancy H. and Ravi Kanbur. 2010. "Turning a Blind Eye: Costly Enforcement, Credible Committment, and Minimum Wage Laws," *Economic Journal*, Vol. 120, Is. 543.

Binswanger, Hans P. and Mark R. Rosenzweig. 1986. *Contractural Arrangements, Employment and Wages in Rural Labor Markets in Asia.* Yale University Press, New Haven, CT.

Blalock, Garrick, and Paul J. Gertler. 2004. "Learning from exporting revisited in a less developed setting," *Journal of Development Economics*, Vol. 75: 397-416.

Blundell, Richard and Stephen Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, Vol. 87.

Blundell, Richard and Stephen Bond. 2000. "GMM Estimation with persistent panel data: an application to production functions," *Econometric Reviews*, Vol. 19, No. 3.

Boal, William M. 1995. "Testing for Employer Monopsony in Turn-of-the-Century Coal Mining," *RAND Journal of Economics*, Vol. 26, No. 3.

Boal, William M. and Michael R. Ransom. 1997. "Monopsony in the labor market," *Journal of Economic Literature*. Vol. 35, No. 1.

Brummund, Peter. 2012. "Evidence on the Impact of Firing Restrictions from Indonesia," *mimeo.*

Burdett, Kenneth and Dale T. Mortensen. 1998. "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, Vol. 39, No. 2.

Ehrenberg, Ronald G. and Robert Smith. 2006. *Modern Labor Economics: Theory and*

Public Policy, Ninth Edition. Reading, MA: Addison Wesley.

Falch, Torberg. 2010. "The Elasticity of the Labor Supply at the Establishment Level," *Journal of Labor Economics*, Vol. 28, No. 2.

Gindling, T.H. and Katherine Terrell. 2005. "The Effect of Minimum Wages on Actual Wages in Formal and Informal Sectors of Costa Rica," *World Development*, Vol. 33, No. 11: 1905-21.

Gindling, T.H. and Katherine Terrell. 2010. "Minimum Wages, Globalization, and Poverty in Honduras," *World Development*, Vol. 38, No. 6: 908-18.

Hallward-Driemeier, Mary, and Bob Rijkers. 2010. "Do Crises Catalyze Creative Destruction? Firm-level Evidence from Indonesia," *mimeo*.

Hansen, Lars Peter. 1982. "Large sample properties of generalized method of moments estimators," *Econometrica*, Vol. 50, No. 3. 1029-54.

Harrison, Ann and Jason Scorse. 2004. "The Impact of Globalization on Compliance with Labor Standards: A Plant-Level Study," in *Brookings Trade Forum 2003* (Susan Collins and Dani Rodrik eds.), Brookings Institution Press, Washington D.C..

Harrison, Ann, and Jason Scorse. 2010. "Multinationals and Anti-sweatshop Activism," *American Economic Review*, 100(1): 247-73.

Hildebrand, George H., and Ta-Chung Liu. 1965. *Manufacturing Production Functions in the United States, 1957*. Ithaca: Cornell University Press.

Hirsch, Barry T. and Edward J. Schumacher. 2005. "Classic Monopsony or New Monopsony? Searching for Evidence in Nursing Labor Markets," *Journal of Health Economics*, Vol. 24, No. 5: 969-89.

Hirsch, Boris, Thomas Schank, and Claus Schnabel. 2010. "Differences in Labor Supply to Monopsonistic Firms and the Gender Pay Gap: An Empirical Analysis Using Linked Employer-Employee Data from Germany," *Journal of Labor Economics*, Vol. 28, No. 2.

Kuhn, Peter. 2004. "Is Monopsony the Right Way to Model Labor Markets? A Review of Alan Manning's Monopsony in Motion," *International Journal of the Economics of Business*, Vol. 11, No. 3.

La Porta, Rafael, and Andrei Shleifer. 2008. "The Unofficial Economy and Economic Development," *Brookings Papers on Economic Activity*. Vol. 39, No. 2: 275-363.

Levinsohn, James and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, Vol. 70.

Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets.* Princeton University Press; Princeton, NJ.

Manning, Chris and Kurnya Roesad. 2007. "The Manpower Law of 2003 and its Implementing Regulations: Genesis, Key Articles, and Potential Impact," *Bulletin of Indonesian Economic Studies*, Vol. 43(1): 59-86

Matsudaira, Jordan D. 2013. "Monopsony in the Low-Wage Labor Market? Evidence from Minimum Nurse Staffing Regulations," *Review of Economics and Statistics* Forthcoming.

Medoff, Marshall H. 1976. "On Monopsonistic Exploitation in Professional Baseball," *Quarterly Review of Economics and Business*, Vol. 16, No. 2.

Olley, G.S. and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, Vol. 64, No. 6.

Persky, Joseph and Herbert Tsang. 1974. "Pigouvian Exploitation of Labor," *The Review of Economics and Statistics*, Vol. 56, No. 1: 52-57.

Pigou, Arthur C. 1924. *The economics of welfare*. 2nd Edition. London: Macmillan and Co.

Ransom, Michael R. and Ronald L. Oaxaca. 2010. "New market power models and sex differences in pay," *Journal of Labor Economics*, Vol. 28, No. 2: 267-89.

Ransom, Michael R. and David P. Sims. 2010. "Estimating the Firm's Labor Supply Curve in a 'New Monopsony' Framework: School Teachers in Missouri," *Journal of Labor Economics*, Vol. 28, No. 2: 331-55.

Robinson, Joan 1933. *The Economics of Imperfect Competition*, Macmillan, London UK

Roodman, David. 2006. "How to do xtabond2: An introduction to "Difference" and "System" Gmm in Stata," *Center for Global Development Working Paper*, No. 103.

Scully, Gerald W.. 1974. "Pay and Performance in Major League Baseball," *American Economic Review*, Vol. 64, No. 6.

Staiger, Douglas, Spetz, Joanne and Ciaran Phibbs. 2010. "Is There Monopsony in the Labor Market? Evidence from a Natural Experiment," *Journal of Labor Economics*, Vol. 28, No. 2: 211-36.

Sullivan, Daniel. 1989. "Monopsony Power in the Market for Nurses," *Journal of Law and Economics*. Vol, 32, No. 2.

Thurow, Lester C. 1974. "Disequilibrium and the Marginal Productivity of Capital and Labor," *The Review of Economics and Statistics*, Vol. 56, No. 1: 23-31.

Udry, Chris. 1996. "Gender, agricultural production, and the theory of the households," *Journal of Political Economy*, Vol. 104: 1010-46.

Webber, Doug. 2011. "The Impact of Firm Market Power on the US Earnings Distribution," *mimeo.*

Windmeijer, Frank. 2005. "A finite sample correction for the variance of linear efficient two-step GMM estimators," *Journal of Econometrics*. Vol. 126.

Van Biesebroeck, Johannes. 2007. "Robustness of Productivity Estimates," *Journal of Industrial Economics*. Vol. 40, No. 3: 529-69.

Zimbalist, Andrew. 1992. "Salaries and Performance: Beyond the Scully Model," in *Dia-*

monds are Forever: The business of baseball. Ed. Paul M. Sommers. Washington DC: Brookings Instiution.

Table 1: Summary Statistics of All Indonesian Manufacturing Establishments

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

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

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

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

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

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

	Passed Spec. Tests		Did Not Pass		
	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 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 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 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)	0.098	(0.007)	0.078	(0.030)	
Product Mkt HHI - Low	-0.047		-0.104**		-0.033	
	(0.081)		(0.044)		(0.024)	0.020
Product Mkt HHI - High	-0.010		0.007		0.033	
	(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 7: 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.