Evidence of Monopsony in the Labor Market of a Developing Country

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Abstract Firms are able to behave monopsonistically because of frictions in the labor market. While there is evidence that these frictions lead to labor market power in specific cases in developed countries, this paper argues these frictions are much more evident in developing countries and therefore monopsonistic behavior is more likely to occur. This paper measures monopsony by structurally estimating the production functions of manufacturing establishments in Indonesia and comparing the resulting marginal revenue product of labor of each establishment to the wages that it pays its workers. This paper finds that establishments do not pay their workers competitively and then analyzes the relative importance of market and establishment specific characteristics in influencing monopsonistic behavior.

Keywords: Monopsony; Labor Markets; Indonesia.

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1 Introduction

This paper will attempt to show that firms[1] in developing countries do not pay their workers according to traditional economic theory of a competitive labor market. The concept of labor markets not being competitive is not new, with Joan Robinson (1933) being credited as the originator of the idea that firms may have some market power over their workers. This paper takes a direct approach at testing for monopsony by measuring the marginal revenue product of labor for manufacturing establishments in Indonesia and comparing it with the wages of each firm. The difference between these two values is the surplus generated by the labor employed at that firm. According to classical economic theory, the firm should pay the worker their marginal revenue product. This paper first documents that firms do not behave according to what competitive theory would predict, and then analyzes the relative importance of market and establishment specific characteristics in influencing monopsonistic behavior.

Monopsony is a useful explanation of labor markets that exhibit frictions in their operation. Traditionally, this meant that there was only one employer of labor in a market and workers had no choice but to work for that employer once they decided to enter the labor force. A mining firm in a small town is a common example of this traditional type of monopsony. In this case, in order for the firm to grow larger, it needs to increase its wage in order to attract more people into the labor force.

This market characteristic also applies to labor markets for specific occupations. For example, school districts are the sole employers of teachers within a given geographic area. While the school district is not the only employer in the area, they are the only employer of a certain type of worker. In order for those employers to expand their labor force, they need to pay a higher wage to attract workers to change occupations or to change locations. This argument can be extended to the developing country context where establishments may

[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

exhaust the supply of a certain quality of worker. For example, a manufacturing firm may require its workers to have a high school diploma, but the local education systems may not be producing enough high school graduates for the firm to employ. Therefore, if the firm wants to employ more workers, it would need to pay higher wages to attract high school graduates from another region, or to incentivize youth to stay in school and obtain their high school diploma.

The literature has more recently started to use monopsony in a firm-specific sense, applying it to situations whenever the labor supply curve to a firm is upward sloping. Burdett and Mortensen (1998) have shown that search frictions lead to upward sloping labor supply curves. They used search frictions in the form of information asymmetries between firms, unemployed job searchers, and on-the-job searchers. Manning (2003) has expanded this to show that many types of search frictions can lead to upward sloping labor supply curves to an individual firm. For example, there could be frictions that limit the mobility of workers between firms, whether they are preferences of the workers for one firm over another or limitations imposed by government policies. Mobility between firms might also be constrained by information asymmetries, where workers are not fully informed about their other options. This might be especially true of labor markets in developing countries where information does not flow quite as well as it does in developed countries, and workers may not know what the wages are in other firms.

Other sources of monopsony power include differentiation between firms or efficiency wages (Boal and Ransom 1997). The differentiation argument is that if firms differ along characteristics over which workers have heterogenous preferences, than firms will have to pay a compensating differential to attract workers that have less of a preference for the particular characteristics of that firm. This leads to an upward sloping labor supply curve. Also, if firms face decreasing returns to scale in their ability to monitor workers, then as firms get larger, they will have to increase the wage to maintain the same punishment for shirking, resulting in a increasing labor supply curve to the firm.

A theoretical critique of the search friction based monopsony model of Burdett and Mortensen is that the upward sloping labor supply curve depends on the assumption of firms having increasing recruiting costs (Kuhn 2004). This assumption may not be very realistic in a developed country context where it may be argued that firms could find it easier to recruit workers as they get larger. However, firms in developing countries often start off by recruiting workers from within their network of family and friends. As firms seek to expand, they need to switch to more formalized recruiting practices which may not be as mature as they are in developed countries. As mentioned above, it is also common for firms in developing countries to not be able to find sufficient numbers of workers with the required levels of skill or education. Firms wanting to grow larger often have to face the decision of investing significant resources in providing a lot of training to local workers, or in hiring workers from other regions and providing transportation and lodging. In either case, growing firms are faced with increasing recruiting costs in developing countries which provides a basis for the assumptions needed by the theoretical model for monopsony.

Understanding whether firms behave monopsonistically or not is important as it determines the wages that employees are paid. If firms behave competitively, workers will get paid according to their marginal revenue product. If firms behave monopsonistically, firms will hire fewer workers at lower wages, both outcomes negatively impacting the welfare of workers. Evidence in support of monopsony would provide rationale for policy makers to impose a minimum wage, as the minimum wage would increase efficiency by both raising workers wages and increasing the number of people employed.

This paper continues in the next section by further discussing the literature surrounding monopsony and the various techniques used to identify monopsony. Section 3 then discusses the empirical techniques used in this paper to measure monopsony. Section 4 introduces the data and provides some descriptive statistics. Section 5 shows the basic results of whether firms behave competitively and also analyzes the relative importance of market and establishment specific characteristics in influencing monopsonistic behavior. Section 6 concludes.

2 Literature Review

Joan Robinson is credited with first discussing the idea of imperfect competition in labor markets (1969). 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 L, and not constant. From here, Pigou's measure of exploitation can be formed:

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

The terms can be rearranged to show that $E = \epsilon^{-1}$ where ϵ is the elasticity of the labor supply curve[2]. In the competitive framework, this elasticity is infinity, which implies that Pigou's measure would be equal to zero. If firms are behaving monopsonistically, the upward sloping labor supply curve would imply a value for the elasticity to be much less than infinity, and then Pigou's measure would be strictly positive.

In this static context, monopsony is most often estimated by regressing log wages on log employment with various controls. Since firms choose labor and wages simultaneously, this approach is identified through the use of firm level instruments that affect firm size without impacting wages. Examples of this approach include Sullivan's study of nurses (1989), Boal's study of coal-mining towns in West Virginia (1995), and Staiger, Spetz, and Phibbs' study of nurses (2010) among others. Most of these studies routinely find that the short-run labor supply elasticity to the firm is low, in the range of 0.1 to 1.27, though Boal's study of miners finds less support. He argues that this is due to the coal mines intentionally working to overcome the moving costs by providing lodging for its workers.

Monopsony can also be considered in a dynamic framework, incorporating search costs.

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

This strand of the literature is based on Burdett and Mortensen's model of job search (1998). Manning developed this approach further by noting that the wages and number of employees a firm chooses depends on the flow of workers into and out of the firm (2003). These models are able to generate an upward sloping labor supply curve in the presence of search frictions or information asymmetries that prevent workers from leaving and arriving at firms at the same rate. In this framework, monopsony can be estimated from estimates of the quit rate of firms. This approach has been taken by Ransom and Oaxaca in their study of discrimination in grocery store workers (2010), and also by Ransom and Sims in their study of public school teachers (2010). Both studies find elasticities of labor supply in the range of 1.5 to 4.

In their comprehensive review, Boal and Ransom (1997) discuss another approach to measuring monopsony, and that is to directly compare the marginal revenue product of a firm to its wage. The key to this approach is the measure of the marginal revenue product of labor, which is dependent on the firm's production function. Boal and Ransom note that this approach has primarily been used in the context of professional athletes where there is reasonably good sense of the production function and detailed data to measure that production (Scully 1974 and Medoff 1976). These studies find a range for the elasticity of labor supply between 0.14 and 1. However, recent advances in the estimation of production functions in industries besides professional baseball allow me to use this approach for this study.

3 Empirical Approach

Since it is common for establishment data to have information on wages paid to workers, the key step in this analysis is to develop a credable estimate for the marginal revenue product of labor for firms. I will describe my approach to obtaining such an estimate in this section. The general idea is to estimate a firm's production function using the approach based on Blundell and Bond's 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, and finally connect the two strands by explaining the different assumptions behind each technique.

Most of the literature uses a Cobb-Douglas production function $Y_{it} = L_{it}^{\beta_L} K_{it}^{\beta_K}$, where Y_{it} is the output of firm i at time t, L_{it} is the amount of labor used in production and K_{it} is the capital. β_j is the factor share of factor j. The most direct way to estimate this is to convert to logs and estimate the equation:

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

were 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 firms choice of inputs and the firm's output. These factors are most often labeled firm specific productivity and incorporated into the model as:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \omega_{it} + \nu_{it}, \tag{1}$$

with ω_{it} representing firm-specific productivity and ν_{it} capturing any measurement error or optimization errors on the part of the firm. Olley and Pakes model the evolution of productivity as a first-order Markov process, assuming that firm's expectations about future production, ω_{it+1} only depend on the current realization of productivity, ω_{it}. However, this equation is also not identified as firms observe their firm specific productivity at the same time as they choose their inputs.

Olley and Pakes developed one approach for breaking this endogeneity by making two key assumptions. The first assumption is that capital evolves deterministically based on investment, $k_{it} = \kappa(k_{it-1}, i_{it-1})$. This means that period t capital stock was actually determined at time $t-1$. The second assumption is that investment is strictly increasing in productivity,

$i_{it} = f_t(\omega_{it}, k_{it})$. This monotonicity allows Olley and Pakes to invert the function, and get the unobservable term ω_{it} in terms of the observables i_{it} and k_{it}. Substituting the expression for ω_{it} into equation (1) yields,

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + f^{-1}(i_{it}, k_{it}) + \nu_{it}, \tag{2}$$

This is Olley and Pakes' first stage, which they argue yields an unbiased estimate of β_L, which is what I need for this analysis. They go on to provide an unbiased estimate of β_K as well, but that is not needed for this analysis, so I will forego those details. With an estimate of β_L, I can derive an estimate for the marginal revenue product of labor,

$$\widehat{R'(L)} = \frac{\partial Y}{\partial L} = \frac{\hat{\beta}_L Y}{L}. \tag{3}$$

Levinsohn and Petrin advance Olley and Pakes' technique by noting that investments often appear in the data as zeros, which gets those observations thrown out of Olley and Pakes' approach. Levinsohn and Petrin use Chilean manufacturing data, and over half of their sample has zero investment. They propose to use intermediate materials to break the endogeneity between productivity and input choices instead of investment. This method also produces an unbiased estimate for β_L in the first stage.

Ackerberg, Caves and Fraser have recently written that both of the above techniques suffer from collinearity problems (2010). They argue that if investment or intermediate materials are functions of both capital and productivity, it is reasonable to assume that the choice of labor must also be a function of the same variables in some form. They argue that this problem is most pronounced in the Levinsohn and Petrin technique since intermediate materials are less likely to move independently of labor than does investment. Their solution is to still use two stages, but to get the estimates for β_L and β_K both in the second stage. They introduce an intermediate stage between t and $t-1$, which they call $t-b$. Productivity evolves in both sub-periods, but capital is determined at time $t-1$, labor is determined at time $t-b$, and intermediate inputs are the most variable, being chosen at time t. These assumptions on the timing of the determination of each of the inputs lead to extra moment conditions that identify the coefficients on each of the inputs in the second stage.

However, when allowing for the possibility for firms to have market power over wages, the firms' choice of labor is now a function of the wage it pays. This means that the labor input choice is chosen endogenously with the error term, net of productivity. The most direct way to correct for this is to instrument for the choice of labor. A common method for obtaining the necessary instruments is to look within the data already on hand, as developed in the dynamic panel data literature.

Blundell and Bond have extended the original dynamic panel data techniques with their system GMM estimator (1998), and have applied it to production functions (2000). This approach deals with the endogeneity of input choices by noting that the variables involved exhibit strong stationarity. This leads the authors to use various instrumental variables based on previous values of the variables. Their approach varies depending on whether the empiricist wants to use firm fixed effects, but the general idea is to use lagged differences as instruments for the current levels of the input variables in addition to lagged levels as instruments for equations in first differences. They also model the evolution of productivity as an AR(1) process, $\omega_{it} = \rho\omega_{it-1} + \eta_{it}$. This approach does have some intuitive appeal, though it places strong requirements on the data, especially if you want to use firm fixed effects, as you will need 3 years of data prior to the year you want to estimate. Their model is:

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

where γ_t is a year fixed effect and δ_i is a firm fixed effect. This is the approach I use the current version of the paper.

Ackerberg, Caves and Fraser also provide a useful comparison of the two approaches to estimating production functions. The first difference is that 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. It is the linearity of the AR(1) process that provides a moment condition used in estimation. A second difference is that Blundell-Bond allow for firm fixed effects, though this puts extra demands on the data. 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 intermediate inputs), 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 esimator provides 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 (2010). 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. However, since the Olley-Pakes approach suffers from collinearity issues and does not handle the endogeneity of the labor choice being a function of the wage, I use the Blundell-Bond approach to estimate the production function for this analysis.

4 Data

The data I use for my 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 1988-2005. There are about 20,000 records each year, but this shrinks as not all of the variables are available every year. This panel dataset includes many variables, but importantly for this study, it has data on output (revenue), inputs, investment, capital, wages, number of employees, ownership, location, industry, etc. A few years of data have more detailed information, such as 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 my 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.

To help identify environments where a classical version of monopsony might occur, I calculate a Herfindahl-Hirschman index for the labor market as $HHI_j = \sum_{i=1}^{N_j} s_i^2$, where s_i is the share of employment at establishment i, and N_j is the number of firms in district j. There are over 550 districts in Indonesia, though I only have data for establishments in about 490 of them. Another common measure of market concentration is the concentration ratio of the x largest firms in the labor market. This is calculated by summing the shares of the x largest firms. Both of these measures range from 0 to 1, and are increasing with concentration.

Summary statistics for the data can be found in Table 1. I display the statistics separately by all firms, foreign owned firms and large domestically owned firms for informational purposes and to help familiarize the reader with the Indonesian context. Each observation is a firm-year. The first row shows the continuous version of the foreign ownership variable, and it shows that if a firm has at least 10% foreign ownership, its likely to have much more than 10%. Also, firms that are classified as not being foreign owned may still have a small

Table 1: Summary statistics of Indonesian Manufacturing Establishments

	All Firms		Foreign Firms		Domestic Firms $\geq$ 250	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
%Foreign	3.98	(17.92)	77.53	(23.69)	0.01	(0.19)
ln(Output)	14.33	(1.97)	16.85	(1.71)	17.11	(1.43)
ln(Input)	13.69	(2.19)	16.26	(1.87)	16.57	(1.64)
ln(Investment)	12.19	(2.71)	14.15	(2.16)	14.10	(2.12)
ln(Capital)	13.46	(2.08)	15.79	(1.91)	15.97	(1.81)
% Output Exported	10.94	(29.71)	37.88	(45.88)	26.83	(42.20)
ln(R&D Exp.)	9.19	(2.22)	10.65	(2.06)	10.47	(2.03)
ln(Value Added/#Emp.)	9.07	(1.16)	10.14	(1.29)	9.53	(1.19)
Firm Age	14.20	(14.42)	11.43	(15.01)	16.74	(16.51)
#Employees	185.98	(665.3)	581.56	(1,147.5)	873.89	(1,533.2)
%Production Wkrs	83.86	(14.13)	82.30	(15.87)	84.10	(15.60)
% w/ HS diploma	27.08	(26.73)	55.49	(28.35)	38.80	(24.90)
% w/ College degree	1.09	(2.71)	2.95	(4.21)	1.49	(2.20)
ln(Wage-Prod)	8.09	(0.69)	8.60	(0.71)	8.32	(0.72)
ln(Wage-NonProd)	8.65	(0.97)	9.53	(1.09)	9.08	(0.97)
Labor HHI - district	0.060	(0.100)	0.046	(0.091)	0.059	(0.103)
Labor 8CR - district	0.269	(0.129)	0.238	(0.102)	0.256	(0.123)
Num	318,388		16,326		39,620	

Notes: All values are in constant 2000 Rupiah. Data covers years 1988 - 2005. Standard deviations are in parentheses. The export data is only available for years 1990-2000, 2004. The R&D expenditure information is available for years 1994-1997 and 1999-2000. The education information is available for years 1995-1997.

amount of foreign influence, though it appears to be minor. About 5% of my observations are for foreign establishments, though they nonetheless follow all the standard results in the literature. They are larger, tend to export more, are more productive, have a more educated workforce, and pay higher wages. The large domestic firms appear to be somewhat more similar to the foreign firms, in terms of size, exports, and the quality of workforce, though they are somewhat older.

5 Analysis

5.1 Estimating the Production Function

My data provide information on production workers separately from non-production workers. As can be seen in the summary statistics above, about 80% of the workers in these manufacturing establishments are production workers, though the non-production workers get paid considerably higher wages on average. This suggests that the labor markets operate separately for these two types of workers. I therefore estimate the production functions using each type of labor as a separate input. The resulting model that I estimate is,

$$y_{it} = \beta_{l^1} l^1_{it} - \rho\beta_{l^1} l^1_{it-1} + \beta_{l^2} l^2_{it} - \rho\beta_{l^2} l^2_{it-1} + \beta_k k_{it} - \rho\beta_k k_{it-1} + \rho y_{it-1} + \mu_{it} \tag{5}$$

As mentioned above, my primary approach for estimating this will be Blundell and Bond's System-GMM estimator, though I will compare the estimates to other techniques. Using equation 5, the System-GMM estimator will produce seven reduced form parameters, $\hat{\pi}$. However, there are really only four structural parameters, $\theta = (\beta_{l^1}, \beta_{l^2}, \beta_k, \rho)$. To recover the structural parameters I use the classical minimum distance estimator,

$$min_{\theta\in\Theta}\{\hat{\pi} - h(\theta)\}'\hat{\Xi}^{-1}\{\hat{\pi} - h(\theta)\}, \tag{6}$$

where $h()$ is the mapping of the between π and θ, and $\hat{\Xi}$ is the weighting matrix. For the weighting matrix, I use the estimated covariance matrix of the reduced form parameters. To get the standard errors for the structural parameters I use,

$$AsyVar(\hat{\theta}) = \frac{1}{n}[\hat{H}'\Phi^{-1}\hat{H}]^{-1}, \tag{7}$$

with $\hat{H}$ being the Jacobian of $h()$. For the weighting matrix Φ, I use the estimated covariance matrix from the reduced form parameters.

With the interest of this analysis being the marginal revenue product of labor, and investigating whether there are meaningful differences in these values across firms, it is important that I allow the β_l parameters to vary as much as possible in my estimation of the production function. To facilitate this, I estimate the production function separately by industry, allowing the firms to have different production functions across industries, but constraining them to be the same within an industry. Table 5.1 displays the results for the estimates of the Cobb-Douglas production function averaged across all the industries to provide a sense of the estimates across the various possible estimation techniques.

An OLS model is estimated in the first row. These results are typically considered to be biased upwards as there is positive correlation between the input choices and the unobserved productivity term. However, with the possibility of monopsony, there could be negative correlation between the labor input choice and the error term as firms with more monopsony power hire fewer workers. The second row presents results for OLS including firm fixed effects. The next row presents results using the Olley-Pakes technique. Following that are results from the Difference-GMM estimator, using lags 2 periods previous and earlier.

The remaining rows present results for various versions of the System-GMM estimator. It is possible to start using lags either 2 or 3 periods previous, with 3 periods previous being superior if you think the 2 period previous may still have some correlation with the error term. The estimator can also generate a lot of instruments which then requires more observations for proper estimation. The last two rows in Table 5.1 shows the results when using just two periods of instruments, either periods 2 and 3, or periods 3 and 4.

The estimates produced by the System-GMM technique are in the ball-park of the other methods. Since I estimate the production function separately by industry, it is important to keep the numbers of instruments down, so I prefer the last two System-GMM estimates over the first. Finally, with the overall approach of this paper being to identify monopsony from looking at the gap between the marginal revenue product of labor and the wage, I want to be conservative with my estimate of the marginal revenue product of labor. With that in

Table 2: Average Cobb-Douglas Production Function Estimates using Various Estimation Methods

Method	β_{PR} (1)	β_{NP} (2)	β_k (3)	Sum (4)
OLS	0.766	0.355	0.126	1.247
OLS-FE	0.645	0.249	0.073	0.967
Olley-Pakes	0.620	0.345	0.154	1.118
BB-Diff2	0.695	0.397	0.117	1.210
BB-System2	0.751	0.448	0.133	1.332
BB-System3	0.717	0.432	0.157	1.306
BB-Sys2-Lo	0.728	0.509	0.114	1.352
BB-Sys3-Lo	0.683	0.461	0.152	1.295

Notes: Average over each industry estimate

mind, I will use the System-GMM-3 estimator in the following analysis of monopsony.

These results differ some from the ranges of the parameters that are common in the estimation of production functions using data from developed countries. The results here have labor shares that are higher and capital shares that are lower. However, this should not be surprising in the developing country context where labor is relatively cheaper, and therefore more likely to appear in the production process. It is also common to see constant returns to scale in the production function. While not shown in Table 5.1, the sum of the coefficients is not statistically significant from one in most of the industries.

There are a couple of other concerns that are important when using the System-GMM technique besides the number of instruments. It is also important that the instruments used are both exogenous and relevant, as is always important when using instruments. This can be tested by using the over-identifying restrictions generated by the instruments and also by looking to see if there is any remaining auto-correlation in the error term. Hansen (1982) has developed a test for the over-identifying restrictions. The remaining error term can also be tested for auto-correlation, the presence of which would indicate the instruments were not exogenous. Arellano-Bond (1991) have developed a test for this.

Table 5.1 presents the results of estimating a Cobb-Douglas production function using

Blundell and Bond's System GMM-3 estimator with a reduced number of instruments. The estimated parameters of the production function are presented for each industry on the left side of the table, and the specification tests are reported on the right side of the table. In the column reporting the t-test of Constant Returns to Scale (CRS), only 2 of the 20 industries are estimated to be significantly different from CRS.

The first specification test reported on the right side of the table compares whether the number of instruments used to the number of firms in the industry. Windmeijer (2005) has done tests on 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 firms. This is true in all the industries except for one, Petroleum and Fuels. Looking at the Hansen test of the over-identifying restrictions for this industry, we see that we get an implausibly high P-value of 1.000, indicating that the technique is not producing reliable estimates for this industry. Looking that the Hansen test for the other industries, we see that in many industries, the instruments are not valid, with P-values near zero, though there are quite a few industries that do have valid instruments. Finally, in the far right-hand column, the P-values for the auto-correlation test of the error-term is reported. In all cases, the error does not exhibit auto-correlation.

5.2 Evidence for Monopsony

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

$$Y = (L_{PR})^{\beta_{l^1}} (L_{NP})^{\beta_{l^2}} K^{\beta_k},$$

Table 3: Cobb-Douglas Production Function Estimates by Industry using System-GMM

Industry	β_{PR}	β_{NP}	β_k	Sum	CRS t-test	Num Firms	Num Instr.	Hansen	AR(1)
Food & Beverage	0.678	0.494	0.085	1.258	1.617	6,185	193	0.000	0.000
Tobacco	1.034	0.111	0.197	1.342	1.493	528	193	0.005	0.000
Textiles	0.623	0.507	0.179	1.309	1.641	2,920	193	0.013	0.000
Apparel	0.746	0.376	0.140	1.263	1.355	2,834	193	0.000	0.000
Leather	0.630	0.559	0.110	1.299	1.307	823	193	0.383	0.000
Wood	0.614	0.391	0.210	1.214	0.996	3,008	193	0.004	0.000
Paper	0.812	0.277	0.262	1.351	1.536	542	193	0.298	0.000
Publishing	0.726	0.591	0.043	1.360	1.664	819	193	0.059	0.000
Petroleum & Fuels	0.208	0.444	0.141	0.792	0.736	62	180	1.000	0.044
Chemicals	0.450	0.629	0.210	1.289	1.438	1,245	193	0.069	0.000
Rubber & Plastics	0.556	0.520	0.155	1.231	1.249	1,986	193	0.153	0.000
Non-metallic Minerals	0.676	0.385	0.238	1.298	1.575	2,516	193	0.023	0.000
Basic Metals	0.695	0.527	0.203	1.424	1.923	387	193	0.582	0.000
Fabricated Metals	0.380	0.545	0.203	1.127	0.566	1,215	193	0.183	0.000
Machinery	0.596	0.533	0.151	1.281	1.032	586	193	0.231	0.000
Electrical Mach.	0.726	0.582	0.050	1.357	1.432	431	193	0.266	0.000
Communication Eq.	0.801	0.438	0.059	1.298	1.238	250	187	0.972	0.000
Motor Vehicles	0.844	0.505	0.186	1.535	2.172	346	193	0.683	0.000
Other Transport.	1.105	0.493	0.076	1.674	3.026	434	193	0.412	0.000
Furniture	0.752	0.309	0.145	1.206	1.027	2,992	193	0.003	0.000

Notes: Results are System-GMM estimates with reduced numbers of instruments. P-Values are listed for specification tests.

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,

$$\frac{\partial Y}{\partial L_{PR}} = \frac{\hat{\beta_{l^1}} Y}{L_{PR}} \tag{8}$$

$$\frac{\partial Y}{\partial L_{NP}} = \frac{\hat{\beta_{l^2}} Y}{L_{NP}} \tag{9}$$

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 $l \in (PR, NP)$. This yields a measure of market power for each firm for each year for both production and non-production workers.

Table 4 provides means of the marginal revenue product of labor and for Pigou's measure of market power. The top panel of the table shows the descriptive results for the production workers and the bottom half for the non-production workers. Results are presented separately for firms in all industries and also for firms in industries where the System-GMM estimator produced credible results. Columns (2) and (3) present the base components of the measure of market power, with the resulting measure displayed in Column (4). The means presented are all weighted by the number of employees in each firm. Columns (5) - (7) display the corresponding labor supply elasticity at the 10th, 50th, and 90th percentiles of the distribution.

Table 4 shows that most firms have considerable amounts of market power, though there is variation in that market power across firms. Remember that if firms are behaving competitively, Pigou's E should be equal to 0 and the labor supply elasticity, ϵ, should be approaching infinity. Comparing the top and bottom panels shows that non-production workers get paid higher wages, but they have much higher MRPL's, and they get less of a share of their MRPL than do the production workers. This suggests that production workers are more able to find another job, while the non-production workers may have more firm-specific human capital that does not carry over to the general labor market as well. This could suggest that the

Table 4: Summary of Pigou's measure of market power assuming all firms in the same industry share a common production function

	N	Wage	MRPL	Pigou's E	ϵ_{10}	ϵ_{50}	ϵ_{90}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prodction Workers							
All firms	318,388	5,066	80,285	43.60	0.030	0.142	0.822
		(6.2)	(501.1)	(5.55)			
Valid firms	33,549	5,624	86,356	40.14	0.031	0.157	0.665
		(21.2)	(1,199.8)	(9.13)			
Non-Production Workers							
All firms	273,820	11,048	279,137	232.83	0.015	0.079	0.658
		(80.5)	(2,712.7)	(47.80)			
Valid Firms	33,549	12,091	332,528	752.14	0.014	0.072	0.702
		(98.6)	(5,946.9)	(169.98)			

Notes: Data covers years 1988 - 2005. The Wage and MRPL values are expressed in thousands of 2000 Rupiah. Means are weighted by the number of employees in each firm. Standard errors are in parentheses.

labor market for non-production workers is more specific that just the geographic district.

Within the top panel, focusing on the results for production workers, we see that the results for the firms in valid industries are not that much different from the overall results. In both cases, the results show that firms are not paying their workers competitively. The bottom panel looks at the results for non-production workers. Here, the results for the valid firms are more different from the overall results, though in both cases there is evidence of significant market power.

5.3 Influences of Market Power

The previous section documented the existence of market power in some labor markets, though they were 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 will take the individual firm-year measurements of market power and regress those on various firm and market characteristics to see which factors influence market power more. I will do this for production workers using a simple GLS model by incrementally adding the various controls. Using the log of Pigou's measure of market power for firm i in labor market j at time t,

$$e_{ijt} = \alpha_0 + \mathbf{X_{ijt}}\boldsymbol{\alpha_1} + \mathbf{Y_{ijt}}\boldsymbol{\alpha_2} + \gamma_j + \nu_i + \epsilon_{ijt}, \tag{10}$$

with $\mathbf{X_{ijt}}$ being a set of time-varying firm characteristics, $\mathbf{Y_{ijt}}$ 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 largest eight firms within the labor market as the time-varying labor market control. 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 and size of the firm as controls, as well as an indicator of whether the firm is foreign owned. Schmieder (2010) has also argued that fast-growing firms are more likely to behave monopsonistically as they have to hire relatively more workers. For this, I use a simple measure of one-year output growth.

It is also possible that the firm has monopoly power in the product market, which could lead it to have inflated values for the marginal revenue product of labor, leading to increased market power as its measured here. To control for this monopoly power in the product market, I calculate the Herfindahl-Hirschman Index by 2-digit industries within each region. Since there are about 30 regions and 20 2-digit industries, I calculated 600 different HHI's for the product market.

Table 5 presents the results of these GLS models where the controls have been entered incrementally. 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.

Table 5: GLS regressions with Pigou's E for Production workers as the dependent variable

	Dependent Var. = ln(Pigou's E)					
	(1)	(2)	(3)	(4)	(5)	(6)
Top 8 Conc. Ratio	2.944**		2.533**	-0.201	1.837**	0.326
	(1.264)		(1.083)	(0.387)	(0.857)	(0.449)
(Top 8 Conc. Ratio)^2	-4.358**		-3.683**	0.266	-4.111***	-0.528
	(1.663)		(1.462)	(0.517)	(1.362)	(0.611)
Foreign		0.284***	0.273***			
		(0.090)	(0.087)			
Firm Age		-0.001	-0.001			
		(0.002)	(0.002)			
ln(Total Emp.)		-0.230***	-0.232***	-0.166***	-0.200***	-0.165***
		(0.028)	(0.028)	(0.022)	(0.035)	(0.022)
ln (Capital)		0.236***	0.235***	0.089***	0.227***	0.090***
		(0.020)	(0.020)	(0.008)	(0.022)	(0.008)
Output Growth		0.000	0.000	0.001*	0.000	0.001*
		0.00	0.00	0.00	0.00	0.00
Monopoly HHI		1.930**	1.792**	0.013	0.459	0.021
		(0.808)	(0.706)	(0.169)	(0.318)	(0.170)
(Monopoly HHI)^2		-1.941**	-1.824***	0.076	-0.843***	0.055
		(0.726)	(0.648)	(0.194)	(0.294)	(0.197)
Constant	1.957***	-0.698**	-1.033***	1.491***	-1.978***	1.372***
	(0.297)	(0.274)	(0.357)	(0.245)	(0.522)	(0.265)
Labor Market Dummies	No	No	No	No	Yes	Yes
Firm Effects	No	No	No	Yes	No	Yes
r2	0.148	0.229	0.233	0.055	0.307	0.062
N	32,934	32,272	32,272	32,934	32,934	32,934

Notes: Data covers years 1988 - 2005. Standard errors are in parentheses. Industry and year dummies are included in all regressions. In models without firm effects, standard errors are clustered at the district level.

Column 1 starts by just including the time-varying market level controls of the concentration ratio of the 8 largest firms, and the square of that term. Both the direct and the square of the labor market concentration ratio are statistically significant, indicating that labor market concentration is positively correlated with market power but at a decreasing rate. The r-squared for this model is 0.148.

Column 2 then looks at the impact of the time-varying firm-level controls (with out including the labor market controls). The results show that foreign-owned firms tend to have more market power, though firm age is not significant. The size of the firm is negatively correlated with market power. This could be capturing the tendency of large firms to be paying higher wages, and being more likely to comply with the wage policies instituted by the government. The amount of capital in the firm is positively correlated with market power. Also, the measures of product market concentration indicate that firms with more product market power also have more labor market power. The r-squared in this model is 0.229, indicating that more of the variation in labor market power can be explained by time-varying firm characteristics than by labor market concentration.

Column 3 then includes both the firm characteristics and labor market characteristics together. None of the controls change their significance level. However, when comparing the r-squared between columns 2 and 3, the additional amount of variation explained upon adding the labor market concentration ratios is minimal. This also suggests that the time-varying firm characteristics are more important in explaining market power.

Column's 4 through 6 then incrementally add the firm fixed effects and the labor market fixed effects. When doing so, I drop the foreign and firm age controls as they would be collinear with the firm fixed effect. Column 4 starts by just including the firm fixed effects. Here, the controls are trying to explain the variation in market power within a firm. The level of market concentration is no longer significant, and actually flips sign. Both the number of employees and amount of capital stay statistically significant. Output growth is now also significant, indicating that if a firm has to grow a lot from one period to the next, it should expect to have more market power, though this could be do to the growing firms having relatively higher levels of productivity.

Column 5 adds the labor market fixed effects. It is more instructive to compare these results with those of column 3. All of the variables stay statistically significant, except for the direct effect of product market concentration. The r-squared also increased by more than it did when moving from columns 2 to 3, indicating the the labor market fixed effects are more important then the time varying labor market characteristics.

Column 6 then includes both the labor market and firm fixed effects. The significance levels are no different than what is reported in column 4. The r-squared increase a bit, but not much.

6 Conclusion

This paper has argued that the labor markets in developing countries are a potentially good context for trying to find evidence of monopsonistic behavior as there are many frictions that could be affecting the movement of workers across firms. 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. I used Blundell and Bond's System-GMM-3 technique for estimating production functions, though other versions are estimated for comparison purposes.

My approach fits the data reasonably well as the estimated production functions are close to exhibiting constant returns to scale, and I find that firms have more market power in areas where there is more concentration in the labor market and less market power in more competitive districts. I find that most firms do have significant amounts of market power, though only few firms are found to not have market power.

I then considered whether a firms 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.

I have already mentioned that future work will incorporate other techniques for estimating production functions, but I also plan on investigating alternative explanations for the wedge between the marginal revenue product of labor and the wage besides monopsony. It could be that firms are paying efficiency wages or there is some sort of firm specific policy distortion of the kind suggested by Bartelsman, Haltiwanger and Scarpetta (2009).

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