Exploitation of Labor?
Classical Monopsony Power and Labor's Share*

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How important is the exercise of classical monopsony power against labor for the level of wages and labor's share? We examine this in the context of China and India – two large, rapidly-growing developing economies. Using theory, we develop a novel method to quantify how wages are affected by the exertion of market power in labor markets. The theory guides the measurement of labor "markdowns," i.e., the gap between wage and the value of the marginal product of labor, and the method examines how they comove with local labor market share. Applying this method, we find that market power substantially lowers labor's share of income: by up to 11 percentage points in China and 13 percentage points in India. This impact has fallen over time in both countries, however.

I. Introduction

Policies affecting labor and wages have increasingly become an important area of concern in many countries as labor's share of aggregate income has fallen. The decline has been observed in many countries and industries, but manufacturing has been hit dispro-

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portionately hard (Karabarbounis and Neiman, 2013). The decline in labor's share over time has been linked to an increase in market power, and measures of market power are closely linked to market concentration (de Loecker, Eeckhout and Unger, 2020). This increase in market power can decrease labor's share through a direct increase in markups, but also through an exercise of monopsonistic market power against labor. Both of these possibilities are of keen policy interest.[1] Apart from isolated cases, however, there has not yet been a method to measure the aggregate importance of increasing market shares and the overall prevalence of employer cooperation on the wages of workers.

This paper develops such a method and applies it to study labor markets in Chinese and Indian manufacturing. Developing countries such as China and India are natural cases to consider. Geographic mobility of labor is low in both countries, hence labor may be more inelastically supplied. Labor in both Chinese and Indian manufacturing is also typically low skilled and less differentiated. Therefore, workers may have less ability to protect themselves against employers. Unions, which are prevalent in India, may play a counteracting force on wages. Their impact on labor's share is less obvious. In addition, the levels of wages for both Chinese and Indian manufacturing workers are low, so that the consequences of lower wages are particularly severe.[2] For all these reasons, it is important to understand labor market power in local Chinese and Indian labor markets.

We develop a method to quantify the levels of monopsony power in the labor market. For the case of the output market (developed in Brooks, Kaboski and Li (2020)), the comovement of markups with a firm's market share is interpreted as the exercise of market power. For the case of cooperation in the input market, the pattern is analogous: markdowns that comove with the firm's own share of the local labor market reflect the exercise of the firm's market power. The coefficients from regressions of markups on market share

[1]See, for example, the U.S. Council of Economic Advisers (2016), which focused on the trends and consequences of labor market monopsony. The labor literature has identified many specific cases of cooperative behavior. Boal and Ransom (1997) provide a nice literature review of labor research on monopsony, and Ashenfelter, Farber and Ransom (2010) provide a somewhat more recent summary. Among others, the cases studied include school teachers and the academic labor market.

[2]Brooks, Kaboski and Li (2020) find evidence in Chinese industrial clusters, especially within officially designated Special Economic Zones (SEZs), of cooperative behavior in the product markets, which in a previous working paper version led us to consider whether firms might cooperate in input markets. The quantitative importance of this was small, however.

and markdowns on labor market share therefore summarize the quantitative importance of market power and identify the key parameters needed for aggregation in the explicit structural model we develop. Using this method, we show that monopsony power substantially lowers labor's share and the level of wages in Chinese and Indian manufacturing.

Naturally, our approach requires a way of identifying the markdown against labor. Gross markdowns are typically defined as the ratio of the value of the marginal product of labor to the wage. However, in a case where firms also markup their output, markups themselves lead the wage to divergence from the value of the worker's marginal product. This is true even for wage-taking firms because the value of marginal product evaluated at the price of output exceeds marginal revenue. The model shows that we can effectively distinguish between an output markup and an input markdown by comparing the ratios of the value of marginal product and the input price across inputs provided the firm is price taking for (at least) one input. For our empirical results, we utilize materials as this input for which firms have no monopsony power. Any monopsony power in materials would lead us to understate the levels of markdowns on labor. Therefore, dividing the labor and materials ratios (a ratio of ratios, with the materials in the denominator), we identify the markdown on labor. That is, the additional proportional deviation between the marginal product and wage identifies the markdown on labor.

We empirically measure markups and markdowns using various approaches that rely on different assumptions. The most common approach to estimate markups is to apply the methods of de Loecker and Warzynski (2012), who in turn utilize the methods of Ackerberg, Caves and Frazer (2015) to estimate the elasticity in the production function. Although increasingly common, this approach has identification issues and requires an assumption of neutral technological progress. Alternative approaches can solve identification problems, and even allow for factor-augmenting technological change, but they require alternative assumptions. Fortunately, we find that estimates using alternative methods are all highly correlated, and our results are broadly robust to differences in measures. Thus, a secondary contribution of this paper is to validate the robustness of these different measures.

We utilize plant-level data from each country, focusing on manufacturing industries. For India, we use the panel version of the Annual Survey of Industry (ASI), a plant-level representative panel covering all large and a sample of smaller plants. These data have the advantage of having plant location, as well as covering the full cross section of manufacturing plants. They have information on output, capital, labor compensation, and materials, data necessary to estimate markups and markdowns. In China, we use the Annual Survey of Chinese Industrial Enterprises (CIE).

Applying our methods, we find evidence that monopsony power in labor markets reduces wages in both China and India. The impact of monopsony power on labor's share is sizable, amounting to roughly 11 percentage points in China and 8 percentage points in India at the beginning of our samples (1999), but falling roughly in half by the end of our samples (2007 in China and 2011 in India). In India, we find that the exercise of market power in the output market (i.e., markups) also has quantitatively important impacts; the total impact of market power in both labor and output markets lowers labor's share in India by as much as 13 percentage points. For comparison, these impacts are much larger than the reported decline of 5 percentage points in the time series of global labor's share over 35 years in Karabarbounis and Neiman (2013).

The overall impacts on the level of wages are also quantitatively important. In India, the impact of the exercise of monopsony power by individual firms in general lowers wages for the average worker by 18 percent. In China, the total effect of monopsony power is to lower wages by about 16 percent. (The impacts on the average worker are much larger than the impacts on the average firm, since the largest firms exercise the most monopsony power.) The burden of monopsony power is not distributed uniformly, however. For example, using our preferred markdown measure, the impact on the average worker in the median labor market in China is just 8 percent, but 10 percent of labor markets have wages lowered by at least 33 percent. These impacts can be substantial, especially in environments where manufacturing wages are already low.

This study contributes to several existing literatures. The paper most closely related is

Brooks, Kaboski and Li (2020). The focus of Brooks, Kaboski and Li (2020) is on product market competition, finding strong evidence of cooperation among firms, especially within Chinese special economic zones. In this paper, we develop analogous empirical methods to quantify the effects of labor monopsony, focusing on the firms' individual exercise of monopsony power and showing that the product market method is robust to the inclusion of labor market power. In follow up work, Brooks et al. (2020) applies this paper's measure to look at the impact of the Golden Quadrilateral highway system in India on the exercise of monopsony power.

The idea that firms might use market power and even collaborate to lower wages is quite old (e.g., Marx, 1867; Malthus, 1798; Smith, 1776). Labor market monopsony has been studied in agriculture in developing countries (Binswanger and Mark R. Rosenzweig, 1984; Braverman and Stiglitz, 1982, 1986) and in particular industries in the U.S. (Lambson and Ransom, 2011; Ransom, 1993). We contribute to this literature, on both the theoretical and empirical side, by developing a more macroeconomic measure of monopsony power and applying it to an entire, new sector (manufacturing) of a large economy.

Monopsony power is the focus of several concurrent studies of the United States. Card et al. (2018), Gouin-Bonenfant (2020), and Lamadon, Mogstad and Setzler (2020) examine the sharing of rents in matching or search labor markets. We study the exertion of classical monopsony power, where workers have no market power of their own. Berger, Herkenhoff and Mongey (2019) study a similar labor market, but they use mergers for identification. Closest is the concurrent work of Hershbein, Macaluso and Yeh (2020), which was written after the working paper version of this paper but developed independently. They develop and apply a similar method for markdowns to the United States. Their method does not use labor market shares directly, however, and simply relies on measured labor wedges, which they find to be larger than ours. Empirically, we are the first to estimate the widespread suppression of wages in a developing country, contributing to a recent literature that has examined the interaction of firm market power and development (e.g., Asturias, Garcia-Santana and Ramos, 2019; Galle, 2020; Itskhoki and Moll, 2019).

The rest of this paper is organized as follows. Section II presents the model, reviews the derivation of the markup method, and derives a generalized formula for testing for monopsonistic power in the hiring of labor. Section III discusses our data and the various markup estimations we consider. Section IV discusses our results for the exercise of monopsony power against labor in Chinese and Indian manufacturing, while Section V concludes.

II. Model

In this section, we present the model of a firm exercising market power in both input and output markets. Although empirically we will focus on labor monopsony, here we develop the model and methods generally for an arbitrary set of inputs.

A. Environment

Consider a large number of industries $i = 1, 2, 3, ...$ and a finite number of locations $k = 1, ..., K$, each containing a finite number, N_{ki}, of firms. Firm n in industry i and location k produces output y_{nki}. Firms face downward-sloping demand curves in output markets.

Production uses a set of inputs indexed by m, where $m = 1...M$, labeled $\{x_{mnki}\}$. Output is given by a production function:

$$y_{nki} = F_i(x_{1nki}, ..., x_{Mnki}; Z_{nki}) \tag{1}$$

where Z_{nki} is a set of firm-level characteristics, including productivity but also any other potential firm or location-specific factors.

Factor markets are segmented by industry and location. Factor prices are determined by an inverse supply function such that the total market supply X_{mki} and price q_{mki} of factor m are both specific to the location k and industry i:

$$q_{mki} = G_{mi}\left(X_{mki}\right), \tag{2}$$

where the aggregate quantity is the sum across all N_{ki} firms in the industry and location:

$$X_{mki} = \sum_{n=1}^{N_{ki}} x_{mnki}. \tag{3}$$

Finally, the firm faces an inverse demand for its output, given the output of all other goods, which we denote $\{y_{jki}\}_{j \neq i}$:

$$p_{nki} = H_i \left(y_{nki}; \{y_{jki}\}_{j \neq i} \right). \tag{4}$$

B. Firm's Problem

Firms maximize static profits by choosing the quantity of inputs and outputs subject to downward-sloping demand curve and an upward-sloping supply for a subset of inputs. Specifically, each firm maximizes:

$$\max_{\{y_{nki}, \{x_{mnki}\}\}} p_{nki} y_{nki} - \sum_{m=1}^{M} q_{mki} x_{mnki} \tag{5}$$

subject to:

$$y_{nki} = F_i(x_{1nki}, ..., x_{Mnki}; Z_{nki})$$

$$q_{mki} = G_{mi} \left(X_{mki} \right).$$

$$p_{nki} = H_i \left(y_{nki}; \{y_{jki}\}_{j \neq i} \right)$$

The fact that p_{nki} and q_{mnki} are both functions in the constraints emphasizes that firms internalize their effect on both output prices and input prices. In particular, by producing more output, they reduce the price of their own output. Similarly, when choosing to use more of an input m, firms internalize its indirect effect on their profits through higher input prices, which allows for the exercise of monopsony power.

If λ_{nki} is the Lagrange multiplier on the production function, the first-order conditions of the firm's problem are:

$$p_{nki} + \frac{\partial p_{nki}}{\partial y_{nki}} y_{nki} = \lambda_{nki} \tag{6}$$

$$q_{mki} + \frac{\partial q_{mki}}{\partial x_{mnki}} x_{mnki} = \lambda_{nki} \frac{\partial F_i}{\partial x_{mnki}} \tag{7}$$

Notice that equations (6) and (7) can be rewritten, respectively, as:

$$\frac{\lambda_{nki}}{p_{nki}} = 1 + \frac{\partial \log(p_{nki})}{\partial \log(y_{nki})} \tag{8}$$

$$\frac{\lambda_{nki} \frac{\partial F_i}{\partial x_{mnki}}}{q_{nki}} = \lambda_{nki} \frac{y_{nki} \frac{\partial \log(F_i)}{\partial \log(x_{mnki})}}{q_{mki} x_{mnki}} = 1 + \frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})} \tag{9}$$

The left-hand side of equation (8) is the inverse (gross) markup, i.e., the ratio of the value of the marginal product to its price. The left-hand side of equation (9) is the (gross) markdown, i.e., the ratio of the value of the marginal product of the input to input price.

We assume the existence of a factor (empirically, we will use materials) for which all firms are price takers. Without loss of generality, we denote this input with the index $m = M$. That is, we assume:

$$\forall n, \frac{\partial \log(q_{Mki})}{\partial \log(x_{Mnki})} = 0 \tag{10}$$

We define a markup μ^M_{nki} as the ratio of output price to marginal cost. Manipulating the equations above, we can solve for the markup making use of the price-taking input as follows:

$$\frac{\frac{q_{Mki} x_{Mnki}}{p_{nki} y_{nki}}}{\frac{\partial \log(F_i)}{\partial \log(x_{Mnki})}} = \frac{1}{\mu^M_{nki}} = 1 + \frac{\partial \log(p_{nki})}{\partial \log(y_{nki})} \tag{11}$$

The left hand term is (the reciprocal of) the familiar expression derived in de Loecker and Warzynski (2012). For the elastically supplied input M, dividing the output elasticity with respect to input M by the expenditure share of revenues of input M gives the markup, which we denote μ_{nki}^{M}. The assumption of one price-taking, flexibly chosen input provides a way of measuring markups in output prices without being confounded by the presence of monopsonistic market power on other inputs.

Moreover, comparing the analogous measure across inputs provides a way of inferring monopsony power in those other inputs. Combining equations (8) and (9) for any input m implies:

$$\mu_{nki}^{m} \equiv \frac{\frac{\partial \log(F_i)}{\partial \log(x_{mnki})}}{\frac{q_{mki} x_{mnki}}{p_{nki} y_{nki}}} = \frac{1 + \frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})}}{1 + \frac{\partial \log(p_{nki})}{\partial \log(y_{nki})}} \tag{12}$$

The term μ_{nki}^{m} is the markup as measured when using input m in the de Loecker and Warzynski (2012) formula of the ratio of the output elasticity to the factor share (denominator). In the absence of monopsony power, using any input implies the same measured markup. With monopsony power, however, this is no longer merely the markup because it contains two components. The first is the standard markup, i.e., distortion of firm production choices, which appears in the denominator of the right hand side, and is the same for all inputs. The second is the distortion due to monopsony power in input market m, which is in the numerator of the right hand side and varies by input. Making use of the special case of input M, where we assume that monopsony power is absent, we note that we can isolate the monopsony power of any input m by writing:

$$\frac{\mu_{nki}^{m}}{\mu_{nki}^{M}} = 1 + \frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})} \tag{13}$$

The left-hand side is therefore a properly normalized measure of the exercise of classical monopsonistic market power. Following the literature, we refer to it as the “markdown”.

Next we make a functional form assumption of the input supply function G_{mi}:

$$G_{mi}\left(X_{mki}\right) = A_{mki}\left(X_{mki}\right)^{\frac{1}{\phi_m}} \tag{14}$$

where A_{mki} is a constant of proportionality and $\phi_m > 0$ measures the elasticity of supply. Then:

$$\frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})} = \frac{1}{\phi_m} s_{nki}^m \tag{15}$$

which we can substitute into equation (13) to yield:

$$\frac{\mu_{nki}^m}{\mu_{nki}^M} = 1 + \frac{1}{\phi_m} s_{nki}^m \tag{16}$$

where we have defined s_{nki}^m as the input share of firm n in the location k- and industry i-segmented market for input m:

$$s_{nki}^m = \frac{q_{mki} x_{mnki}}{\sum_l q_{mki} x_{mlki}}. \tag{17}$$

This generates a linear equation that will become the basis for our estimation and will be used to quantify of the exercise of market power. We note an important implication that is common to both markups and markdowns. If firms are behaving independently, whether in their markups or their markdowns, the measured markups and markdowns will depend on the relevant share of their own firm, their market share in the product market in the case of monopoly power or their market share in the input market in the case of monopsony power.

The results for monopsony power stand alone, but we can generate a corresponding equation to estimate monopoly power by choosing a functional form of output demand. In particular, we choose a nested constant elasticity inverse demand expression:

$$p_{nki} = \left(\frac{y_{nki}}{Y_i}\right)^{-1/\sigma}\left(\frac{Y_i}{D_i}\right)^{-1/\gamma} \tag{18}$$

where D_i is an exogenous industry-level demand parameter and industry output, Y_i, is given by:

$$Y_i = \left(\sum_{k=1}^{K}\sum_{n=1}^{N_{ki}} y_{nki}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{19}$$

Hence, $\sigma > 1$ captures the within industry elasticity while $\gamma > 1$ captures the between industry elasticity. We assume that $\sigma > \gamma$ reflecting that goods are more substitutable within industries than industries are with one another. Substituting these into (19), we can write the equations for (inverse) markups as a linear function of market shares:

$$\frac{1}{\mu_{nki}^{M}} = 1 - \frac{1}{\sigma} - \left(\frac{1}{\gamma} - \frac{1}{\sigma}\right) s_{nki} \tag{20}$$

where s_{nki} are the firms' shares in output markets. When the firm's market share is 1, the markup is set according to the between-industry elasticity σ, while when it is 0, it is set according to the within-industry elasticity γ. This is a useful expression of evaluating the impact of market power on markups.

C. *Calculating Aggregate Labor's Share*

We now depart from our general formulation and consider the specific case of labor, which we denote with superscript L. Moreover, the superscript M will now denote materials (or total intermediates). We define the labor share as total payments to labor divided by value added and denote it η_L:

$$\eta_L = \frac{\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} q_{Lnki} x_{Lnki}}{\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} (p_{nki} y_{nki} - q_{Mnki} x_{Mnki})} \tag{21}$$

The labor share of a given firm in the national labor pool is:

$$\omega^L_{nki} = \frac{q_{Lnki} x_{Lnki}}{\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} q_{Lnki} x_{Lnki}} \tag{22}$$

Then notice by taking the reciprocal of the labor share, we can derive an expression that depends on firm-level labor shares of the national labor pool, and ratios of input expenditure to revenue:

$$\frac{1}{\eta_L} = \sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \frac{p_{nki} y_{nki}}{q_{Lki} x_{Lnki}} \omega^L_{nki} - \sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \frac{q_{Mki} x_{Mnki}}{q_{Lki} x_{Lnki}} \omega^L_{nki} \tag{23}$$

Finally, notice that the ratios of input expenditure to revenue appear in the definitions of the markups. That is:

$$\mu^L_{nki} \equiv \frac{\theta^L_{nki}}{\frac{q_{Lki} x_{Lnki}}{p_{nki} y_{nki}}}, \qquad \mu^M_{nki} \equiv \frac{\theta^M_{nki}}{\frac{q_{Mki} x_{Mnki}}{p_{nki} y_{nki}}} \tag{24}$$

where for any input m,

$$\theta^m_{nki} \equiv \frac{\partial \log(F_i)}{\partial \log(x_{mnki})}. \tag{25}$$

These imply that:

$$\frac{p_{nki} y_{nki}}{q_{Lki} x_{Lnki}} = \frac{\mu^L_{nki}}{\theta^L_{nki}}, \qquad \frac{p_{nki} y_{nki}}{q_{Mki} x_{Mnki}} = \frac{\mu^M_{nki}}{\theta^M_{nki}} \implies \frac{q_{Mki} x_{Mnki}}{q_{Lki} x_{Lnki}} = \frac{\mu^L_{nki} \theta^M_{nki}}{\mu^M_{nki} \theta^L_{nki}} \tag{26}$$

Finally, this can be substituted into equation (23) to get:

$$\frac{1}{\eta_L} = \sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \left[\frac{\mu^L_{nki}}{\mu^M_{nki}} \frac{\mu^M_{nki} - \theta^M_{nki}}{\theta^L_{nki}} \omega^L_{nki} \right] \tag{27}$$

Notice that this equation is only rearranging definitions, and does not require any assumptions on functional forms or market structure. We can use this to perform various counterfactuals. In particular, since $\frac{\mu^L_{nki}}{\mu^M_{nki}}$ is the gross markdown, adjusting this by subtracting out the role of market power in the labor market, i.e., $\frac{1}{\phi_m} s^m_{nki}$ in equation (16) gives labor's share when monopsony power has been eliminated.[3] Similarly, keeping this ratio constant, but adjusting μ^M_{nki} by subtracting out $\left(\frac{1}{\gamma} - \frac{1}{\sigma}\right) s_{nki}$ (see equation (20)) yields the impact of market power in the product market on labor's share. Note that these are simple accounting counterfactuals. Changing prices and wages has a direct effect on market shares and labor market shares, but we do not account for any general equilibrium impacts on demand patterns. For such counterfactuals, a full specified general equilibrium model with explicit assumptions on market structure would be necessary.

III. Empirical Approach

This section discusses our empirical implementation, including data, several alternative methods for estimating markups, and our model-derived estimation of the exercise of market power.

A. Data

Our empirical applications are in China and India. The data for China come from the Annual Survey of Chinese Industrial Enterprises (CIE), while the data for India come from the Annual Survey of Industries (ASI). All data sources satisfy the requirements to construct markups, including those that utilize production function estimation following

[3]Note that in theory this is equivalent to setting the markdown to one for all firms. In practice, there may be other things driving measured wedges away from zero that are not related to market power in the labor market as discussed in Section III.C.

the standard methods of Ackerberg, Caves and Frazer (2015). Specifically, they are panel data containing information on revenue, labor, and capital. They also contain data on industry and location, which is necessary to construct labor market variables.

The CIE is conducted by the National Bureau of Statistics of China (NBSC). The database covers all state-owned enterprises (SOEs), and non-state-owned enterprises with annual sales of at least 5 million RMB (about $750,000 in 2008).[4] It contains the most comprehensive information on firms in China. These data have been previously used in many influential development studies (e.g., Hsieh and Klenow (2009), Song, Storesletten and Zilibotti (2011)) Between 1999 and 2007, the approximate number of firms covered in the NBSC database varied from 162,000 to 411,000. The number of firms increased over time, mainly because manufacturing firms in China have been growing rapidly, and over the sample period, more firms reached the threshold for inclusion in the survey. Since there is a great variation in the number of firms contained in the database, we used an unbalanced panel to conduct our empirical analysis.[5] For industry, we use the adjusted 4-digit industrial classification from Brandt, Van Biesebroeck and Zhang (2012). We construct real capital stocks by deflating fixed assets using investment deflators from China's National Bureau of Statistics and a 1998 base year.

For India, we use the ASI as our primary source because it contains a measure of plant location. India's Annual Survey of Industries is collected by their Ministry of Statistics and Programme Implementation and has recently been made available in a panel format. Although it lacks information on ownership, it has the advantage of being plant level data, so we have some information on the actual location of production. It also has somewhat broader coverage. The data contains all large firms (greater than 50 employees) and a sample of smaller firms that depends on the industry and the number of firms within that

[4]We drop firms with less than ten employees, and firms with incomplete data or unusual patterns/discrepancies (e.g., negative input usage). The omission of smaller firms precludes us from speaking to their behavior, but the impact on our proposed methods would only operate through our estimates of market share and should therefore be minimal.

[5]The Chinese growth experience necessitates that we use the unbalanced panel. Using a balanced panel would require dropping the bulk of our firms (from 1,470,892 to 60,291 observations), or shortening the panel length substantially.

industry and state. (We use sampling weights consistently in all of our analysis). Between 1999 and 2011, the approximate number of establishments contained in the sample varies from 23,000 to 44,000. Instead of sales, we have the value of gross output, while we replace material expenditures with the total value of indigenous and imported items consumed. Labor payments include the sum of wage, bonus, and contribution to provident and other funds, while for the capital stock, we use the value of fixed assets, net of depreciation. As with China, we focus only on the manufacturing sector and focus on 4-digit manufacturing industries.

The panel data in both cases are high quality and have been used in many studies. Nevertheless, we note two important caveats relevant to our study.

First, in both countries, our panel datasets disproportionately cover larger firms. They therefore cover a relatively large share of aggregate manufacturing gross output, about 76 percent in China and 72 percent India according to available data.[6] The share is relatively stable for India (fluctuating between 67 and 76 percent, with no clear correlation with our results). It is more difficult to assess in China, given the limited years, but it also does not show a trend. Since larger firms tend to have higher productivity, however, our data constitute a markedly lower fraction of the overall employment in manufacturing, about 37-43 percent in China and only 14-20 percent in India. The remaining employment is held by small firms, many of which are informal. If the output and labor markets for formal and informal firms were close substitutes, we would be overestimating our market shares in the output and especially the labor markets. If instead, they are relatively segmented, our measures of market shares may be more accurate.

Second, measurement of materials is crucial in two of our three measures of markups, which are inputs into our measures of markdowns. In the Chinese data, the CIE measures materials as all expenditures on intermediates. The measure of materials in the Indian data includes expenditures on all indigenous and imported goods (raw materials, components,

[6]These data come from the Reserve Bank of India and from Chinese Statistical yearbooks. The aggregate data for China are much more limited, since they typically report the "industrial" sector rather than narrow manufacturing. We only have aggregate manufacturing employment data for the early years in our sample, 1999-2002.

chemicals, packing materials, etc.), which entered into the production process of the factory during the accounting year. Any material used in the production of fixed assets (including construction work) for the factory's own use is also included, however. We acknowledge the caveat that slight differences in these definitions may impact direct comparison in markdowns across country.

B. Measuring Markups and Markdowns

In order to implement our tests in Section II, we need measures of markups. These markups will be used directly in our product market analysis, and as part of our measurement of labor markdowns in our labor market analysis. We estimate markups using three different approaches, which we detail here. We then discuss the additional steps needed to estimate the markdown.

The first two approaches to estimate markups utilize the insight of de Loecker and Warzynski (2012), who extend Hall (1987) to show that one can use the first-order condition for any flexibly-chosen, price-taking input to derive the firm-specific markup as the ratio of the factor's output elasticity $\theta_{i,t}^M$ to its firm-specific factor payment share $\alpha_{i,t}^M$:

$$\mu_{i,t}^M = \frac{\theta_{i,t}^M}{\alpha_{i,t}^M}. \tag{28}$$

The flexibly chosen input that we use is materials, and the superscript M signifies this. The factor payment share comes directly from the data, but the output elasticity of materials $\theta_{i,t}^M$ needs to be estimated.

Our first method derives the output elasticity $\theta_{i,t}^M$ from the production function estimation of Ackerberg, Caves and Frazer (2015) as in de Loecker and Warzynski (2012). They estimate translog production functions which can then be used to easily solve for elasticities. This approach is most standard, but it has some important shortcomings, especially when used in conjunction with de Loecker and Warzynski (2012) to estimate markups. The first limitation is that it assumes a production function that is constant across firms (within an industry) and only differs by a factor-neutral productivity parameter. The second limitation is that the production function is, without assuming constant returns to scale, only identified for the case of either a value-added production function or a gross output production function in which materials are Leontieff (see Ackerberg, Caves and Frazer (2015) and also Gandhi, Navarro and Rivers (2016) for a full explanation). Either of these special cases preclude the estimation of the elasticity of output with respect to materials, the precise parameter necessary to apply the de Loecker and Warzynski (2012) formula.[7] Since this is the standard way of estimating markups, however, (e.g., de Loecker and Warzynski (2012), Edmond, Midrigan and Xu (2015), de Loecker et al. (2016), and Brooks, Kaboski and Li (2020)), we present this as one measure, but we allow for several alternatives. In our implementation, we estimate a third-order translog production function at the 2-digit industry level. We label this markup method "DLW", since it most closely follows their implementation.

Our second method uses a completely different approach to estimate markups. Rather than using the DLW approach, we try to estimate the gross profit margin. The gross profit margin is a valid estimate of the markup as long as the production function is constant returns to scale and the firm is price-taking in its inputs (i.e., there is no monopsony power). While this constant returns to scale production function is a strong assumption along one dimension – it assumes that it is downward sloping demand that fully determines the size of the firm – it is less restrictive along other dimensions. It allows for firm-specific production functions that are time-varying, for example. In this sense, it also allows for more general forms of technological change, including factor augmenting technical change.[8] The precise formula we use is:

[7] Gandhi, Navarro and Rivers (2016) augment estimation moments with first order conditions or revenue share equations in order to obtain identification, advancing on Levinsohn and Petrin (2003) and Doraszelski and Jaumandreu (2013), who do this in the context of a Cobb-Douglas production function. Finally, Ackerberg, Caves and Frazer (2015) note that, when prices are observed – as in the case of India but not China – one could construct physical units and use a dynamic panel approach. Moreover, when input prices are available, one can use those as instruments. We perform a version of this below as a robustness estimate of the Cobb-Douglas elasticity.

[8] For this reason, we prefer the gross margin approach to Ackerberg, Caves and Frazer (2015) estimation imposing constant returns to scale.

$$\mu_{i,t}^{M} = \frac{sales}{costs} = \frac{py}{q_K x_K + q_L x_L + q_M x_M}. \tag{29}$$

We can measure sales (py), labor payments ($q_L x_L$), and materials expenditures ($q_M x_M$) directly from the data, but for capital, we have the stock of capital (x_K) rather than the payments to capital ($q_K x_K$). The key therefore is to differentiate payments to capital from profits that stem from markups/market power. Notice that the reason this measure of markups is less appropriate in the presence of markdowns is because it attributes all profits (in excess of returns to capital) to markups (higher revenues per unit of output), while some actually would come from markdowns (lower costs per unit of output).

We discipline the return to capital using the cost of capital measured in the data using $R = r + \delta$. For China, we have interest payments and debt separately which yields a value of $r = 0.10$. In India, we look at the return on corporate bonds, which yields a value of $r = 0.08$. To both of these we assume a standard depreciation rate of $\delta = 0.05$ to yield R values of 0.15 for China and 0.13 in India. This yields an average markup of 1.13 in China and 1.16 in India. We label this second markup measure as "CRS", which stands for the constant returns to scale assumption.

Our third method, uses an intermediate approach: we use the markup formula in equation (28), but rather than using an estimate of the elasticity, $\theta_{i,t}^{M}$, it simply assumes that the production function is Cobb-Douglas with respect to materials, i.e., $\theta_{i,t}^{M} = \theta^{M}$. We make a strong assumption on functional form, and we lose some interpretation, but the lack of identification of the production function in Ackerberg, Caves and Frazer (2015) poses no problem for us. We instead choose $\theta^{M} = 0.8$ for China and $\theta^{M} = 0.7$ for India so that the average level of our markups equals the average measured using the CRS method. We refer to this third markup measure as "CD", which stands for Cobb-Douglas.

A preferable alternative to calibrating θ^{M} would be to estimate it directly using an instrument. As in the case of the Ackerberg, Caves and Frazer (2015) estimation, we estimate these coefficients at the 2-digit level of industry. In the Indian data, we have the (logged) price of the primary intermediate input, which we can use to instrument for material expenditures. This yields a very similar estimate of $\theta^M = 0.8$, statistically indistinguishable from our calibrated value. We show that using the estimated value of θ^M yields very similar results for our markdown estimates as shown in Appendix A. Unfortunately, for China, only industry level input price indexes are available. Not only do they not vary across firms, but they only vary across 4-digit industries in 20 out of our 29 2-digit industries. Even in these cases, they are a weak instrument for intermediate use at the firm level, and so not useful. Hence, we proceed with the calibrated θ^M values, but the robustness for India is comforting.

In each case, markups are clearly measured with substantial error. We therefore winsorize 3 percent in both sides of the tails of each 2-digit industry in each year.

Table 1 presents summary statistics for the Chinese and Indian data, and the resulting markup and market share estimates. As can be seen, there is substantial variation in the markup estimates.[9] Market shares are constructed at the national level for 4-digit industries for most of our analyses and the narrow industry classification best reflects the horizontal model of competition. Nevertheless, the market shares tend to be quite small at the firm level. Moreover, the data are positively skewed for every variable, so that medians are much less than means.

Table 2 presents a cross-correlation matrix for the data across the three markup estimates. All three markups are highly correlated with each other, with no correlation falling below 0.5. The fact that the correlation is highest between CD and DLW indicates that independent variation in the elasticity parameter in DLW is relatively small.

The fact that the measures are highly correlated is comforting for the DLW estimates, since it means that the lack of clean identification of the production function does not prevent the estimates from carrying a strong signal. Although they are not perfectly correlated, the estimation results for CD and DLW are almost always the same in terms of their qualitative pattern and statistical significance, and very similar in terms of their

[9] Because the markups are positively skewed, trimming the outliers lowers the average means of the actual data used, and the amount of the decline depends on the variance in the data.

magnitude. Given this, we consider the CD results as our primary benchmark. Much of the results are also robust to the CRS approach as well, which is again comforting. In most cases, the precise variant of markups that we use is relatively unimportant.

To measure monopsony power, we also need to measure markdowns and labor market shares. We measure markdowns by taking the ratio of the labor-based markup (i.e., $\mu^L_{i,t} = \frac{\theta^L_{i,t}}{\alpha^L_{i,t}}$. to the materials-based markup in equation (28). We measure the labor-based markup again using the CD approach, assuming a constant θ^L. We calibrate this elasticity by using the fact that, absent market power in the factor market, the markdown should be one. Thus, we normalize θ^L so that the average markdown for a firm with zero labor market share equals one.[10] We use the unwinsorized markups to compute markdowns, but we then again winsorize the 3 percent tails (within each year and 2-digit industry) based on the overall markdown. Notice in the CD case, that the markdown becomes materials payments over labor payments multiplied by a constant that equals the ratio θ^L/θ^M.

C. Empirical Estimation of Market Power

Our empirical tests draw directly from the optimization relationships derived in Section II. We operationalize these conditions using panel data on firms, using the following equation for firm n, a member of (potential) syndicate S, in industry i at time t. We can estimate monopoly power of firms using the relationship derived in equation (20), empirically implemented as:

$$\frac{1}{\mu^M_{nit}} = \Gamma_t + \alpha_{ni} + \beta s_{nit} + \varepsilon_{nit} \tag{30}$$

Comparing, we see that the estimation adds time dummies Γ_t, firm-specific fixed effects, α_{ni} (which can partially account for firm-specific demand elasticities, see Brooks, Kaboski and Li (2020)), and an error term ε_{nit} that stems from either measurement error or unanticipated shocks. These methods were applied by Brooks, Kaboski and Li (2020) to China,

[10] Concretely, we do this by choosing markups so that the average of the time and firm dummies in equation (30) equals one.

although they also examined cooperative exercise of market power.[11] We show that those estimates are robust to the possible presence of monopsony power, provided the markup is not measured using an input with monopsonistic power.

Similarly, we can estimate the excercise of monopsonistic cooperation in the labor market using:

$$\frac{\mu^L_{nkit}}{\mu^M_{nkit}} = \Gamma_t + \alpha_{ni} + \beta_L s^L_{nkit} + \varepsilon_{nkit} \tag{31}$$

Comparing the two regression equations, (30) and (31), the precise regressions clearly differ, but notice that the identification and intuition behind both the product market and factor market methods are analogous. If firms' markups comove with their product market share over time, this looks like the exercise of market power in the product market, and if we see markdowns comoving with the firm's share in the labor market over time, we attribute this to the exercise of monopsony power.

To develop further intuition for our estimation of monopsony power, consider the markdown measure in the case of a Cobb-Douglas-measured markups, our preferred benchmark. Notice that our markdown measure is nothing more than the ratio of the factor share going to materials over that going to labor (appropriate scaled by the ratio of output elasticities). In research on misallocation (e.g., Hsieh and Klenow (2009)), this ratio measures any unnamed distortion on labor relative to materials. Our assumption that materials is undistorted (flexibly chosen and price-taking), allows us to identify this as a distortion to labor. In general, variation in this ratio, especially cross-sectional variation, could reflect other distortions to the use of labor (e.g., union premia) or firm-specific variation in the importance of labor in technology (e.g., firm-specific Cobb-Douglas exponents on labor).

Another possible interpretation of this "wedge", however, might be that it reflects labor adjustment costs. Notice there are (at least) two interpretations of labor adjustment costs. The first is that new labor is less productive in the short-run, i.e., the output elasticity

[11] An earlier working version of this paper includes estimates of cooperative results, which were only important in China.

of labor is lower in the short-run than in the long run. The Ackerberg, Caves and Frazer (2015) formula uses short-run variation to estimate the labor elasticity, however, so the fact that our results are robust to both measures is comforting on this front. A second is that it is easier to hire labor in the short run than in the long run at a particular wage, so firms need to spend more resources the more additional labor they hire at that wage. Since the alternative to spending these resources would be to increase the wage, this latter interpretation reflects the exercise of monopsony power, i.e., keeping wages low, when an increase in wages would be needed to hire more workers.

We address adjustment costs in two ways. First, we make use of the results in Hershbein, Macaluso and Yeh (2020) that derive a formula for markups in the presence of quadratic adjustment costs.[12] Specifically, suppose that changing labor from l_{-1} last period to l this period imposes a cost to the firm equal to:

$$\Phi(l, l_{-1}) = \psi \frac{l}{2} \left(\frac{l - l_{-1}}{l_{-1}} \right)^2 \tag{32}$$

They assume that firms make dynamic decisions to maximize their risk neutral present value with constant discount rate β. Then they demonstrate that the relationship between markdowns and the elasticity of labor supply is given by:

$$1 + \frac{s^L_{nki}}{\phi_L} = \frac{\frac{\mu^L_{nki}}{\mu^M_{nki}} - \psi(g_l(1 + g_l) - \beta \mathbf{E}[g_{l'}(1 + g_{l'})(1 + g_{sw'})|z])}{1 + \frac{\psi}{2} g_l^2}, \tag{33}$$

where g_l is the growth rate of labor this period, $g_{l'}$ is the growth rate of labor next period and $g_{sw'}$ is the growth rate of the labor bill next period. Following Hershbein, Macaluso and Yeh (2020) we set ψ, the level of adjustment costs, to 0.185 and β, the discount factor, to one so that the adjustment costs are relatively important. Leveraging the panel aspect of our data, we can measure these growth rates explicitly and use this formula to adjust

[12]For example, Petrin and Sivadasan (2013) attribute sizable wedges between wage and marginal products to hiring and firing costs. These linear costs lead to inaction regions that are complicated to characterize, so we stick with convex costs.

our markdown measures to account for adjustment costs. We do this and estimate our main results again using these adjusted markdown measures. These results are given in Table 6. Compared to the results in Table 5, we can see that the estimates are similar in magnitude and significance but the point estimates are consistently approximately 10 percent smaller. This demonstrates that adjustment costs account for some variation in our measured markdowns, but explain only a small part of our results.

Second, we try a less structural approach to distinguish between short-run impacts like labor adjustment costs and the long-run impacts of the exercise of monopsony power: we time difference equation (31) using a longer four-year difference. Changes over four years are less likely to reflect short-term adjustment costs.

Finally, our theory also helps us to isolate the part of these markdowns (or labor wedges) that reflect monopsony power. Namely, the intercepts on average ought to equal unity – firms with zero share in the labor market should exhibit no classical monopsony power and hence a unitary markdown. In practice, estimates using the raw markdowns exceed unity, however. In practice there is also considerable measurement error in the estimation of markups themselves. Since these markups are in the denominator, the convex relationship of $1/\mu^M_{nit}$ leads to markdowns measures that are much larger than one on average.[13] This is one reason that the level of raw markdowns (captured by the intercepts and fixed effects) will be less informative than the increase in markdowns coming from market power (captured by the $\beta_{1,L} s^L_{nkit}$ term). We therefore rescale markdowns so that the average intercept equals 1.[14] Again, examining equation (31) further, rescaling assures us that eliminating the component of this markdown that covaries with labor market share (capturing the exercise of labor market power) is equivalent to setting the average markdown to one.

An additional task is to define the appropriate labor market. We consider labor markets to be segmented both geographically and by type of work. Geographically, we view

[13]This is simply Jensen's inequality. The expectation of the markdown can be expressed as $E(\mu^L/\mu^M) = E(\mu^L)E(1/\mu^M) - cov(\mu^L, 1/\mu^M)$. Since the markup μ^M_{nit} is inside the convex function 1/x, classical measurement error will raise the average markup.

[14]This underscores a strong reason for adding firm-specific fixed effects in our regression equation (31), so that our estimate of the exercise of firm monopsony power is based on within-firm panel variation.

provinces as the natural choice for China and states as the natural choice in India. In China, cross-province migration is regulated by the Houkou system, while in India cross-state migration is quite low (Munshi and Rosenzweig, 2016). Regarding type of work, we assume that workers have a degree of specialization and therefore cannot perfectly move across industries. Of course, the assumption of labor supply elasticity can be interpreted as allowing some movement of workers across sectors, rather than workers merely increasing their own individual labor supply. We consider 2- , 3-, and 4-digit industries as boundaries, and our results are fairly robust to this choice.

Table 3 presents summary statistics for these markdown and labor market shares in the Chinese CIE and Indian ASI data. The average values of the markdowns, which are the most important averages are small, averaging 3 percent in China across all three measures, and 1 percent in India. Note that our rescaling of the numbers is quantitatively important here, but substantial variation exists. Without rescaling these numbers would be much larger.[15] We have noted the strong skew in the values, so that medians are much less than average markups. Given our focus on aggregates, targeting the average markdown is the appropriate method to rescale. Similarly, firms' share of the labor market are also small, averaging less than 1 percent when defined as all workers in a 2-digit sector and only 3-6 percent when using a 4-digit sector to define a labor market. Nonetheless, substantial variation again exists.

Finally, for the monopsonistic regression, notice that the firm's labor payments are in the denominator of markdowns and also the numerator of market shares. Measurement error in labor payments, which certainly exists, will bias our estimates downward. We therefore instrument for labor market share in equation (31). The instruments we use are lagged labor market share and the current revenue share of a firm within the labor market, $s^*_{nki} = \frac{p_{nki}y_{nki}}{\sum_l p_{lki}y_{lki}}$. Table 4 gives an example of this first stage regression. The R^2 is extremely high given firm-level fixed effects, but, more importantly, the two instruments

[15]In the U.S., for example, Hershbein, Macaluso and Yeh (2020) attribute the full wedge to monopsony power and find numbers of roughly 2.

explain roughly two-thirds of the remaining variation.[16]

IV. Results

We present the results in three steps. First, we examine the evidence for exertion of monopsony power in the labor market using the CIE and ASI data. Throughout our regression analysis, we report robust standard errors, clustered at the firm level. Next, we consider the exertion of market power in the product market, which can also affect labor's share. Finally, we present the aggregate results for labor's share implied by our estimates based on equation (27).

A. Monopsony in the Local Labor Market

We present the results for exertion of monopsony power in labor markets using the estimation in equation (31). We run the tests using all three markdown measures, and the full set of manufacturing firms. These results are presented in Table 5. The top panel presents the results for China, while the bottom presents the results for India. Going across the columns, the regressions vary in their measurement of markups (and markdowns) and in their industry definition of the local labor market.

In all the columns, the significant coefficients on labor market share are all correctly signed, regardless of the measure for markups or the level of labor market segmentation along different lines. Moreover, the magnitudes of the estimates are robust to the way in which markups (and markdowns) are measured, but they vary considerably over the assumed level of labor market segmentation.

Focusing on the implied elasticity of labor supply parameter, ϕ, all estimates are significant and range between 0.4 to 2.5, within the range of standard estimates for long run labor supply. Nevertheless, they are larger, the narrower the definition of the labor market. One interpretation of the upward sloping supply of labor is that none of these labor markets

[16] Although both instruments are significant and have explanatory power, product market share is the stronger of the two. Indeed, results using only product market share in an earlier version of the paper produced very similar results.

is strictly segmented. The pattern in estimates are thus consistent with easier movement across narrow industries than across broader industries, and hence a higher elasticity of labor supply in narrowly defined industries. These patterns give us confidence that the regressions are picking up the mechanism at play.

In sum, we find evidence that firms exert monopsony power against labor. In addition, the implied labor supply elasticities are reasonable.

As discussed in Section III.C, one possible interpretation of these results is that the measures reflect adjustment costs on labor, and we discussed our structural and reduced form approaches to accounting for adjustment costs. Table 6 shows the results where the markdowns are net of the calibrated adjustment costs in equation (33). We find that the results after accounting for adjustment costs are lower than the baseline but by a quantitatively small amount. The estimates are similar in magnitude and significance but the point estimates are consistently approximately 10 percent smaller. This suggests that adjustment costs explain only a small part of our results.

Our reduced form approach is to examine four-year differences in the data, and these results are presented in Table 7. Naturally, this involves dropping much more data, so the sample sizes are substantially smaller. Nevertheless, the results are robust to this differencing. The significance of the coefficients shows a very similar pattern, with own share being strongly significant in both China and India. The magnitudes of the coefficients are also quite similar, as are the implied labor supply elasticities. Finally, the robustness of the results to the way that markups and markdowns are measured holds in the differenced sample as well, as does the larger labor supply elasticity estimates for narrower industries. In sum, it does not appear that our results are driven by short-run labor adjustment costs.

B. Market Power in Product Markets

Another way that firm concentration can impact labor's share is through its effect on markups. We turn now to the evidence of how market share impacts markups using the estimation in equation (30). Table 8 presents the results using 2-, 3-, and 4-digit industries as a product market definition for India and China.[17] In all columns, the coefficients on product market share are correctly signed, but are not precisely estimated. We note, also, that relative to China, the estimates of β_1 are substantially larger for India when using 3- or 4-digit sector to define the product market. This indicates that Indian firms can exercise substantial market power for a given market share. This may be the result of lower demand elasticities (compare the coefficient on market share with Equation (20) in India) or simply that competition is not truly national among Indian manufacturers, as we have assumed. In that case, we have underestimated the relevant market shares of our firms, and correspondingly overestimated the coefficients. In either case, however, the net effect, i.e., the product of β_1 and market share, is what drives the additional markup, and those are quite similar regardless of how we define markets.

C. Aggregate Impact of Market Power on Wages and Labor's Share

In this section we present the results for the impact of monopoly and monopsony power on wage levels and conclude with aggregate impact of concentration on the level and trends in labor's share.

The estimates in Tables 5-7 have implications for the impact of market concentration on wage levels themselves. We run two counterfactuals: (i) eliminating markdowns related to market power in the labor market, and (ii) eliminating markdowns related to market power in the labor market and markups related to market power in the product market. The first counterfactual involves creating a counterfactual markdown series as the markdown series in equation (31) with $\beta_L = 0$ by subtracting out $\hat{\beta}_L s^L_{nkit}$. Since gross markdowns are typically defined as the ratio of the value of the marginal product of labor to the wage, we can write the relative wage gains as the ratio of original gross markdown to the counterfactual gross markdown. The precise equation that we use to compute the percentage impact of

[17] Brooks, Kaboski and Li (2020) run similar regressions for China using the CIE data, but they also look for cooperative market power. They found that firms exercise market power both individually, and to a substantial degree they cooperate with other firms in their county and 4-digit industry. An earlier working paper version of this paper found no evidence of cooperation in Indian product or labor markets, and even the quantitative impact of cooperation in the Chinese labor and product markets was quantitatively small.

monopsony power on wage, w, is as follows:

$$
(34) \qquad \frac{\tilde{w}}{w} - 1 = \frac{\displaystyle\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \frac{\mu^L_{nkit}}{\mu^M_{nkit}}}{\displaystyle\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \left(\frac{\mu^L_{nkit}}{\mu^M_{nkit}} - \hat{\beta}_L s^L_{nkit} \right)} - 1
$$

where $\tilde{w}$ is the counterfactual wage. We present two different numbers. The first uses raw summations, while the second weights firms by their employment. For the raw summation formulas, recall that, given our rescaling normalization, the average markdown for a firm with zero labor market share equals one.[18] Then the denominator in equation (34) is equal to the total number of firms in the sample. In this first case, the impact on wages is just the average markdown, and it has the interpretation as the wage gain for the average firm. In the weighted case, the formula is no longer as direct, but it has the interpretation of the wage gain for the average worker, or, equivalently, the aggregate wage gain.

The second counterfactual is to evaluate the impact of both market power-driven markups and markdowns on the wage level. If all markups and markdowns were driven by market power, this would simply equal the average μ^L. However, μ^L could be driven by many things, and we want to only eliminate the ability to exert market power, i.e., the power coming from non-zero market shares. To do this, we decompose μ^L into two terms which can easily be adjusted, $\mu^L = \left(\frac{\mu^L}{\mu^M}\right)\left(\mu^M\right)$. The first term is the markdown, and we create a counterfactual markdown series as above. The second term is the markup, and we create a counterfactual markup series with $\hat{\beta} = 0$ in an analogus fashion by subtracting out $\hat{\beta} s_{nit}$ using the inverse markup formula in equation (20). The formula for computing percentage

[18] This is distinct from eliminating all variation across firms, which we feel is inappropriate to evaluate the exercise of labor market power. Using the Cobb-Douglas case as an example, eliminating all variation in the ratio of material payments to labor payments across firms would also eliminate other sources of misallocation, and any other source of differences, that vary at the firm level.

wage gains becomes:

$$(35) \qquad \frac{\tilde{w}}{w} - 1 = \left(\frac{\displaystyle\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \frac{\mu^L_{nkit}}{\mu^M_{nkit}}}{\displaystyle\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \left(\frac{\mu^L_{nkit}}{\mu^M_{nkit}} - \hat{\beta}_L s^L_{nkit} \right)} \right) \left(\frac{\displaystyle\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \mu^M_{nkit}}{\displaystyle\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \left(\frac{1}{\frac{1}{\mu^M_{nkit}} - \hat{\beta} s_{nit}} \right)} \right) - 1$$

We again present numbers for raw summations and employment-weighted summations. The former is the wage increase for the average firm, while the latter is the wage increase for the average employee.

Table 9 presents the relative wage gains from these counterfactuals. (We restrict our results to our benchmark, the Cobb-Douglas estimates, but all are quite similar.) We see that in both countries, the labor market power drives the results. In China, wages would be up to 2.8 percentage points higher, while in India, they would up to 1.2 percentage points higher. The effect of product market power is smaller in both countries: negligible in China, while contributing to about 0.3 percentage points in India. The employment-weighted results are substantially larger than the raw results, however. We find that the employment-weighted wage gain from eliminating monopsony power is about 16 percent in China and 18 percent in India. This is intuitive, since the largest firms tend to have the largest market share in their labor markets and therefore exercise the most monopsony power.

Table 10 examines the variability of these wage gains across labor markets. Wage gains for the average firm in the median labor market are small, roughly 1.3 percent in China and 0.6 percent in India, but they are substantial in the 10 percent of markets where labor market concentration is highest, about 7 percent of wages in China and 2.2 percent in India. Again, looking at the impact on the average worker, these gains can be quite large, averaging 15.9 and 17.9 percent for the average labor market, but up to at least 33.5 percent for the top 10 percent most affected markets in China, for example. Thus, these wage gains can be substantial. We turn now to their impact on aggregate labor's share.

We start by examining the patterns for concentration over time in China (1999-2007) and India (1999-2011). Figure 1 presents Herfindahl indexes for local labor markets and national product markets in China and India over time. Both countries have a high level of concentration in the local labor market, but very little national concentration in product markets. However, the time patterns are different with China showing a substantial decline in both labor and product markets, while India stays relatively flat throughout the sample period. (In interpreting these patterns, however, we repeat our caveat that our data cover larger firms, especially in China.)

Given the estimates above, we follow the accounting in equation (27) in order to estimate the quantitative importance of our monopsony and monopoly power estimates for labor's share. Recall that it is an accounting equation and is therefore independent of any assumptions on market structure, but also reflects a partial equilibrium thought experiment, abstracting from changes in the reallocation of labor that might come from output or input price changes. We focus on the Cobb-Douglas estimates which are both identified and internally consistent with the presence of monopsony power. The results are presented in Figure 2. China is presented on the left and India on the right. The solid lines present the actual pattern of labor's share, which declined about 4 percentage points in China, and oscillated in India over the relevant periods.

In China, if firms had no market power at all in the labor market akin to price takers in wages, our partial equilibrium counterfactual indicates that labor's share would have been about 11 percentage points higher in the beginning of the period but only 5 percentage points higher at the end of the period. This is consistent with the falling labor market concentration in Figure 1. The impact of product market power on labor's share is negligible in China. The counterfactual labor's share is largely unchanged when we introduce the additional impact of market power in the product market.

In India, the dashed line counterfactual shows that without any monopsony power, our partial equilibrium counterfactual indicates that labor's share in India would have been as much 8 percentage points higher in 2001, although the impacts falls to about 4 percentage points by the end of the sample. Comparing this dashed line counterfactual to the dashed-dot line counterfactual shows the additional impact of product market power on labor's share. The impact of product market power on labor's share is between 5 and 6 percentage points over the sample period. Without either source of concentration driven market power, labor's share would have been 13 percentage points higher (in 2001), and falling to about 9 percentage points by 2011.

These impacts are substantial and swamp the overall time series patterns of labor's share for both these countries, and for other advanced economies as in Karabarbounis and Neiman (2013) that have garnered much attention.

V. Conclusion

We have developed a simple empirical method for quantifying the impact of market power in the labor market. In both India and China, we find strong evidence of monopsony power in the labor market. These have substantial impacts on the levels of wages and labor's share, although the impacts have declined over time. We also showed that both the product market and labor market estimation methods are robust to various ways of measuring markups.

Future work in this area should consider the relationship between market power exercised in output markets and input markets. One possibility is that lower monopsony power alone would be tempered by higher monopoly power in general equilibrium. To see this, recall that output markups are increasing in output market share. Empirically, market share in output markets and input markets are positively correlated. Hence, if monopsony power was eliminated (for example, suppose labor supply elasticities grew to infinity) large firms would disproportionately increase their input usage relative to small firms.[19] Then larger firms increasing their share of input usage implies that they would therefore increase their market share in output markets. Since output market shares are, in turn, directly related to

[19] To see this, recall that monopsony power causes larger firms to restrict their input usage by more than smaller firms. Hence, eliminating monopsony power causes larger firms to increase their input usage by more than smaller firms.

output markups, this implies that any change in input market competition should directly affect output markups, and vice versa. Therefore, future work should study the relationship between these outcomes, and the crucial elasticities are for determining the magnitude of these effects.

Finally, the methods developed in this paper can be applied specifically to study the effects of particular policies on labor markets by comparing our derived measures in places that were and were not exposed to policy changes. As an example, in onoing work Brooks et al. (2020) applies these methods to the expansion of highway systems to see how market access affects competition. We believe that using the tools developed here to study such policies is a promising avenue for future work.

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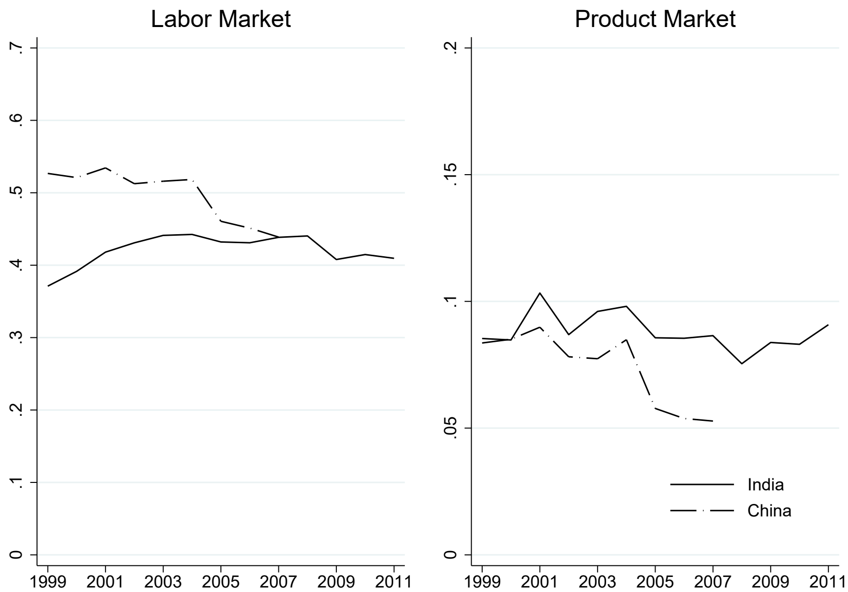
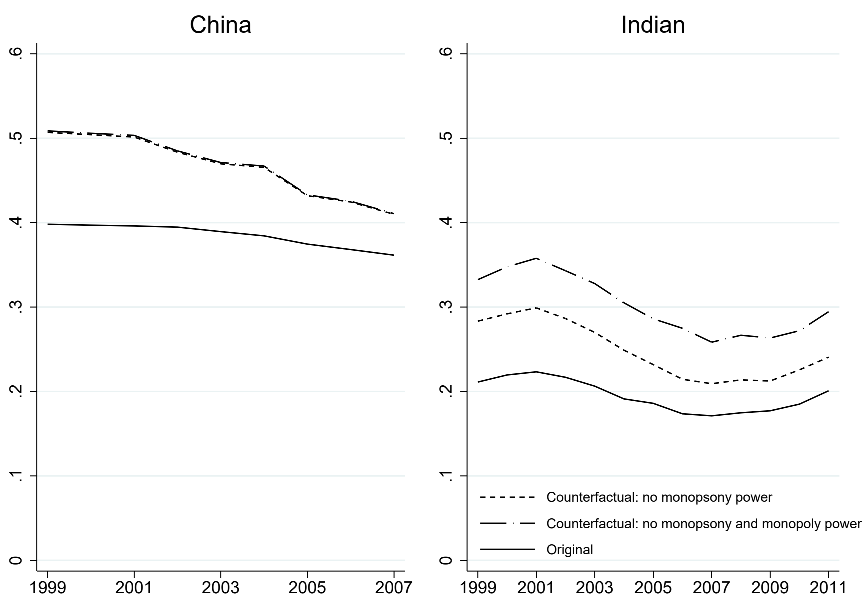
Figure 1. Concentration measured using the Herfindahl Index



Notes: The herfindahl index is constructed using the winsorized sample. The estimates for India are weighted by the ASI-provided sampling weights.

Figure 2. Labor Share Counterfactuals



Notes: The estimates are constructed using equation (27) with the Cobb-Douglas-measured markups. The industry aggregation is defined at the 4-digit level. The estimates for India are weighted by the ASI-provided sampling weights.

Table 1—Key Summary Statistics of Data

	Mean	Median	SD	Min	Max
Panel A: China CIE					
Markup (DLW)	1.27	1.24	0.19	0.75	3.73
Markup (CD)	1.13	1.10	0.16	0.87	3.92
Markup (CRS)	1.13	1.12	0.17	0.47	3.23
Firm Share	0.003	0.0006	0.015	0	1
Real Capital per Firm (000s RMB)	306	46	3,361	0.01	753,064
Real Materials per Firm (000s RMB)	648	157	5,156	0.01	849,709
Real Output per Firm (000s RMB)	888	224	6,881	0.02	1,230,552
Workers per Firm	295	120	1,028	10	166,857
No. of firm-year obs			1,182,929		
Panel B: India ASI					
Markup (DLW)	1.36	1.24	0.52	0.02	15.77
Markup (CD)	1.04	0.93	0.40	0.01	10.54
Markup (CRS)	1.16	1.13	0.33	0.01	5.24
Firm Share	0.001	0.0001	0.011	0	1
Real Capital per Firm (000s Rs)	454	19	9,590	0.00	3,402,507
Real Materials per Firm (000s Rs)	1,144	97	25,106	0.00	12,858,844
Real Output per Firm (000s Rs)	1,555	121	33,970	0.00	18,601,728
Workers per Firm	79	21	448	1	121,007
No. of firm-year obs			386,377		

Notes: Market shares are computed using 4-digit industries. Capital, materials, and output are in thousand Rupees/RMB (in real value). The table winsorizes the 3 percent in both sides of the markup estimates of each 2-digit industry in each year.

Table 2—Cross-correlation Matrix across Three Markup Estimates

	Markup (DLW)	Markup (CD)
Panel A: China CIE		
Markup (CD)	0.81	
Markup (CRS)	0.62	0.54
Panel B: India ASI		
Markup (CD)	0.90	
Markup (CRS)	0.72	0.73

Notes: The table winsorizes the 3 percent in both sides of the markup estimates of each 2-digit industry in each year.

Table 3—Summary Statistics of Markdown and Labor Share

Variable	Mean	Median	SD	Min	Max
Panel A: China CIE					
Markdown (DLW)	1.03	0.61	1.24	0.05	17.71
Markdown (CD)	1.03	0.60	1.22	0.05	16.16
Markdown (CRS)	1.03	0.63	1.13	0.11	14.73
Labor Market Share (2 digit)	0.007	0.001	0.036	0	1
Labor Market Share (3 digit)	0.030	0.004	0.101	0	1
Labor Market Share (4 digit)	0.062	0.008	0.164	0	1
No. of firm-year obs			1,182,928		
Panel B: India ASI					
Markdown (DLW)	1.01	0.51	1.46	0.001	15.67
Markdown (CD)	1.01	0.49	1.51	0.002	15.49
Markdown (CRS)	1.01	0.53	1.40	0.053	14.25
Labor Market Share (2 digit)	0.006	0.0004	0.040	0	1
Labor Market Share (3 digit)	0.014	0.001	0.071	0	1
Labor Market Share (4 digit)	0.024	0.002	0.098	0	1
No. of firm-year obs			386,377		

Notes: The table winsorizes the 3 percent in both sides of the markdown estimates of each 2-digit industry in each year.

Table 4—First Stage: Predicting Labor Share

	(1)	(2)	(3)	(4)	(5)	(6)
		China CIE			India ASI	
	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit
Product Market Share	0.719***	0.811***	0.835***	0.584***	0.664***	0.714***
	(0.016)	(0.005)	(0.003)	(0.020)	(0.010)	(0.007)
Lagged Labor Share	0.063***	0.054***	0.046***	0.191***	0.145***	0.108***
	(0.013)	(0.004)	(0.002)	(0.016)	(0.008)	(0.006)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	672,012	672,006	671,991	145,245	145,245	145,245
Adjusted R-squared	0.935	0.930	0.937	0.944	0.953	0.955

Notes: This table presents the relationship between labor market share with product market share and lagged labor market share, controlling for year and firm fixed effects. We define labor markets at the province level for China and state level for India. Various industry aggregation levels are employed, including 2-digit industry (in specifications 1 and 4), 3-digit industry (in specifications 2 and 5), and 4-digit industry (in specifications 3 and 6). Regressions about India are weighted by the ASI-provided sampling weights. Robust standard errors clustered at firm level are in parentheses. Significance: ***: 1%, **: 5%, *: 10%.

Table 5—Baseline Results about Monopsony Power

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit
	Markdown (DLW)			Markdown (CD)			Markdown (CRS)		
Panel A: China CIE Sample, 1999-2007									
Firm's Share	2.373***	0.818***	0.445***	2.504***	0.851***	0.462***	2.206***	0.752***	0.408***
	(0.191)	(0.037)	(0.019)	(0.201)	(0.037)	(0.019)	(0.181)	(0.034)	(0.018)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	672,012	672,006	671,991	672,012	672,006	671,991	672,012	672,006	671,991
First-stage F	1,218	14,827	43,511	1,218	14,827	43,511	1,218	14,827	43,511
ϕ	0.421***	1.223***	2.246***	0.399***	1.175***	2.163***	0.453***	1.329***	2.454***
	(0.034)	(0.055)	(0.098)	(0.032)	(0.052)	(0.091)	(0.037)	(0.061)	(0.108)
Panel B: India ASI Sample, 1999-2011									
Firm's Share	1.138***	0.746***	0.525***	1.017***	0.686***	0.473***	0.903***	0.612***	0.423***
	(0.132)	(0.067)	(0.038)	(0.128)	(0.067)	(0.037)	(0.116)	(0.061)	(0.034)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	145,245	145,245	145,245	145,245	145,245	145,245	145,245	145,245	145,245
First-stage F	1,079	3,589	7,279	1,079	3,589	7,279	1,079	3,589	7,279
ϕ	0.878***	1.340***	1.906***	0.983***	1.459***	2.112***	1.107***	1.635***	2.365***
	(0.102)	(0.120)	(0.138)	(0.124)	(0.142)	(0.163)	(0.143)	(0.163)	(0.189)

Notes: This table presents the estimates from equation (31). We define labor markets at the province level for China and state level for India. We use three different markup measures, including markup(DLW) (in specifications 1-3), markup(CD) (in specifications 4-6), and markup(CRS) (in specifications 7-9). Various industry aggregation levels are employed, including 2-digit industry (in specifications 1, 4, and 7), 3-digit industry (in specifications 2, 5, and 8), and 4-digit industry (in specifications 3, 6, and 9). Regressions about India are weighted by the ASI-provided sampling weights. Robust standard errors clustered at firm level are in parentheses. Standard errors on ϕ are computed using the delta method. Significance: ***: 1%, **: 5%, *: 10%.

Table 6—Effect of Monopsony Power Accounting for Adjustment Costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit
	Markdown (DLW)			Markdown (CD)			Markdown (CRS)		
Panel A: China CIE Sample, 1999-2007									
Firm's Share	2.050***	0.678***	0.372***	2.201***	0.719***	0.391***	1.945***	0.635***	0.345***
	(0.226)	(0.044)	(0.024)	(0.239)	(0.045)	(0.024)	(0.216)	(0.042)	(0.022)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	373,873	373,869	373,865	373,873	373,869	373,865	373,873	373,869	373,865
First-stage F	645.9	9,047	25,617	645.9	9,047	25,617	645.9	9,047	25,617
ϕ	0.488***	1.474***	2.687***	0.454***	1.392***	2.556***	0.514***	1.574***	2.901***
	(0.054)	(0.096)	(0.175)	(0.049)	(0.087)	(0.158)	(0.057)	(0.103)	(0.189)
Panel B: India ASI Sample, 1999-2011									
Firm's Share	0.959***	0.646***	0.446***	0.821***	0.570***	0.384***	0.711***	0.502***	0.335***
	(0.134)	(0.067)	(0.040)	(0.123)	(0.064)	(0.036)	(0.113)	(0.059)	(0.034)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	100,080	100,080	100,080	100,080	100,080	100,080	100,080	100,080	100,080
First-stage F	747.5	2,456	4,884	747.5	2,456	4,884	747.5	2,456	4,884
ϕ	1.043***	1.549***	2.240***	1.219***	1.755***	2.606***	1.406***	1.993***	2.984***
	(0.146)	(0.160)	(0.200)	(0.183)	(0.196)	(0.245)	(0.223)	(0.234)	(0.302)

Notes: This table presents the estimates from equation (31) and we use equation (33) to adjust the markdown measures to account for adjustment costs. We define labor markets at the province level for China and state level for India. We use three different markup measures, including markup(DLW) (in specifications 1-3), markup(CD) (in specifications 4-6), and markup(CRS) (in specifications 7-9). Various industry aggregation levels are employed, including 2-digit industry (in specifications 1, 4, and 7), 3-digit industry (in specifications 2, 5, and 8), and 4-digit industry (in specifications 3, 6, and 9). Regressions about India are weighted by the ASI-provided sampling weights. Robust standard errors clustered at firm level are in parentheses. Standard errors on ϕ are computed using the delta method. Significance: ***: 1%, **: 5%, *: 10%.

Table 7—Effect of Monopsony Power using Four-year Differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit
	ΔMarkdown (DLW)			ΔMarkdown (CD)			ΔMarkdown (CRS)		
Panel A: China CIE Sample, 1999-2007									
ΔFirm's Share	1.718***	0.708***	0.426***	1.771***	0.729***	0.436***	1.542***	0.648***	0.388***
	(0.297)	(0.070)	(0.038)	(0.304)	(0.071)	(0.039)	(0.275)	(0.065)	(0.036)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	91,403	91,403	91,401	91,403	91,403	91,401	91,403	91,403	91,401
First-stage F	278.4	2,430	6,859	278.4	2,430	6,859	278.4	2,430	6,859
ϕ	0.582***	1.413***	2.346***	0.565***	1.372***	2.292***	0.649***	1.544***	2.574***
	(0.101)	(0.139)	(0.212)	(0.097)	(0.133)	(0.205)	(0.116)	(0.156)	(0.239)
Panel B: India ASI Sample, 1999-2011									
ΔFirm's Share	1.428***	0.816***	0.596***	1.306***	0.762***	0.554***	1.165***	0.681***	0.496***
	(0.211)	(0.100)	(0.058)	(0.198)	(0.100)	(0.057)	(0.179)	(0.092)	(0.052)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	47,956	47,956	47,956	47,956	47,956	47,956	47,956	47,956	47,956
First-stage F	259.8	1,011	2,142	259.8	1,011	2,142	259.8	1,011	2,142
ϕ	0.700***	1.226***	1.678***	0.766***	1.312***	1.804***	0.858***	1.468***	2.016***
	(0.104)	(0.151)	(0.163)	(0.116)	(0.173)	(0.184)	(0.132)	(0.198)	(0.211)

Notes: This table presents the estimates from a time-differenced equation (31) using a four-year difference. We define labor markets at the province level for China and state level for India. We use three different markup measures, including markup(DLW) (in specifications 1-3), markup(CD) (in specifications 4-6), and markup(CRS) (in specifications 7-9). Various industry aggregation levels are employed, including 2-digit industry (in specifications 1, 4, and 7), 3-digit industry (in specifications 2, 5, and 8), and 4-digit industry (in specifications 3, 6, and 9). Regressions about India are weighted by the ASI-provided sampling weights. Robust standard errors clustered at firm level are in parentheses. Standard errors on ϕ are computed using the delta method. Significance: ***: 1%, **: 5%, *: 10%.

Table 8—Effects of Monopoly Power

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit	2-digit	3-digit	4-digit
	Markup (DLW)			Markup (CD)			Markup (CRS)		
Panel A: China CIE Sample, 1999-2007									
Firm's Share	-3.810***	-0.487***	-0.107***	-0.873***	-0.103**	-0.020	-10.378***	-1.504***	-0.434***
	(0.603)	(0.081)	(0.017)	(0.244)	(0.042)	(0.013)	(1.474)	(0.201)	(0.031)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,079,957	1,079,957	1,079,957	1,079,957	1,079,957	1,079,957	1,079,957	1,079,957	1,079,957
Adjusted R^2	0.550	0.550	0.550	0.460	0.460	0.460	0.572	0.572	0.572
Panel B: India ASI Sample, 1999-2011									
Firm's Share	-2.442***	-0.757***	-1.262*	-4.581***	-1.187***	-1.952**	-9.384***	-2.989***	-5.134*
	(0.695)	(0.159)	(0.675)	(1.333)	(0.202)	(0.996)	(2.715)	(0.518)	(2.687)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	328,432	328,432	328,432	328,432	328,432	328,432	328,432	328,432	328,432
Adjusted R^2	0.613	0.613	0.614	0.627	0.627	0.627	0.599	0.599	0.602

Notes: This table presents the estimates from equation (30). Market shares are computed based on a national product market. We use three different markup measures, including markup(DLW) (in specifications 1-3), markup(CD) (in specifications 4-6), and markup(CRS) (in specifications 7-9). Various industry aggregation levels are employed, including 2-digit industry (in specifications 1, 4, and 7), 3-digit industry (in specifications 2, 5, and 8), and 4-digit industry (in specifications 3, 6, and 9). Robust standard errors clustered at firm level are in parentheses. Regressions about India are weighted by the ASI-provided sampling weights. Significance: ***: 1%, **: 5%, *: 10%.

Table 9—Monopsony and monopoly effect on wage

	Simple average	Size-weighted average
Panel A: China CIE		
Monopsony effect	0.028	0.159
Monopsony and monopoly effect	0.029	0.160
Panel B: India ASI		
Monopsony effect	0.012	0.179
Monopsony and monopoly effect	0.015	0.255

Notes: This table presents the estimates from equation (34) and equation (35). The estimates use the Cobb-Douglas-measured markups and the industry aggregation level is 4-digit. The table presents two kinds of the estimates: one uses raw summations, and the other one weights firms by their employment.

Table 10—Distribution of monopsony effect on wage across labor markets

	Mean	Median	p75	p90
Panel A: China CIE				
Simple average	0.028	0.013	0.036	0.070
Size-weighted average	0.159	0.083	0.235	0.335
Panel B: India ASI				
Simple average	0.012	0.006	0.013	0.022
Size-weighted average	0.179	0.131	0.192	0.242

Notes: This table presents the estimates from equation (34) across labor markets in China and India. The estimates use the Cobb-Douglas-measured markups and the industry aggregation level is 4-digit. We define labor markets at the province level for China and the state level for India. The table presents two kinds of the estimates: one uses raw summations, and the other one weights firms by their employment.

Table A—Robustness check using alternative markup estimates

	(1) 2-digit	(2) 3-digit	(3) 4-digit	(4) 2-digit	(5) 3-digit	(6) 4-digit
	Markdown CD (baseline)			Markdown CD (IV)		
Firm's Share	1.017***	0.686***	0.473***	1.032***	0.579***	0.389***
	(0.128)	(0.067)	(0.037)	(0.131)	(0.071)	(0.040)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	145,245	145,245	145,245	138,265	138,265	138,265
First-stage F	1,079	3,589	7,279	1,005	3,422	6,975
ϕ	0.983***	1.459***	2.112***	0.969***	1.726***	2.574***
	(0.124)	(0.142)	(0.163)	(0.123)	(0.211)	(0.263)

Notes: This table presents the estimates from equation (31) using the Indian ASI data. Columns 1-3 repeat the estimates in Table 5 using the Cobb-Douglas-measured markups. Columns 4-6 use the markup estimates from an instrumental variable regression. We use the log price of the firm's biggest material input as an instrument for materials to recover the share parameter in the Cobb-Douglas (CD) case. We define labor markets at the state level for India. Various industry aggregation levels are employed, including 2-digit industry (in specifications 1 and 4), 3-digit industry (in specifications 2 and 5), and 4-digit industry (in specifications 3 and 6). All regressions are weighted by the ASI-provided sampling weights. Robust standard errors clustered at firm level are in parentheses. Standard errors on ϕ are computed using the delta method. Significance: ***: 1%, **: 5%, *: 10%.