# 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 screen to quantify how wages are affected by market power exerted in labor markets, either by a single firm or a group of cooperating firms. 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 screen examines how they comove with local labor market share and the share of cooperating firms. Applying this test, we find that markdowns substantially lower the labor share: by up to 10 percentage points in China and 15 percentage points in India. This impact has fallen over time in both countries as firm concentration in these labor markets has decreased.*

Policies affecting labor and wages have increasingly become an important policy concern around the world as the labor share of aggregate income has fallen. The decline has been observed in many countries and across industries, but manufacturing has been hit

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disproportionately 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 share (de Loecker and Eeckhout (2017)). 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] The consequences are potentially even higher when firms have greater incentives to cooperate in lowering wages, as alleged in the lawsuit against the major technology firms in Silicon Valley.[2] Apart from these isolated cases, however, there has not yet been a way 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 local labor markets in Chinese and Indian manufacturing. Developing countries such as China and India are natural cases to consider; monopsony could be important for several reasons. The geographic mobility of labor is low in India, and China has the well-known *houkou* system, hence labor may be more inelastically supplied. Labor in Chinese and Indian manufacturing is also typically low skilled and less differentiated. Therefore, workers may have less ability to protect themselves against employers.[3] In addition, both micro and macro data attribute relatively small shares of income paid to labor in both countries. Related, Chinese and Indian manufacturing workers are also low paid, so that the consequences of lower wages are particularly severe. Finally, cooperation may also be present in local labor markets. Brooks, Kaboski and Li (2017) (BKL) find evidence in Chinese industrial clusters, especially within officially designated Special Economic Zones (SEZs), of cooperative behavior in the product markets. Thus, for all these reasons, we may be likely to find quantitatively important effects of labor market power in local Chinese and Indian labor markets.

[1] See, for example, the U.S. Council of Economic Advisers (2016), which focused on the trends and consequences of labor market monopsony

[2] The labor literature has identified other such 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, most of interest to researchers, the academic labor market.

[3] Unions, which are admittedly prevalent in India, especially in certain states like Bengal or Kerala may play a counteracting force on wages. Their impact on labor's share is less obvious.

We develop a method to quantify the levels of monopsony power, including monopsonistic cooperation among firms, in the labor market. For the case of the output market (developed in BKL), the comovement of markups with a firm's market share is interpreted as the exercise of market power, and the comovement of markups with the total market share of the cooperating firms is a collaborative 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, whereas markdowns that comove with the total market share of the cooperating firms in labor market reflect collaborative exploitation of labor market power. The coefficients on a joint regression summarize the quantitative importance of this relationship 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.

Our approach requires a way of identifying the markdown against labor. Markdowns are typically defined as the gap between the wage and the value of the marginal product of labor. However, in a case where firms also markup their output, markups themselves lead to deviations between wages and the value of a workers' marginal product. This is true even for wage-taking firms because the price of output exceeds marginal revenue. The model shows that we can effectively distinguish between a markup and a markdown by comparing the ratios of the value of marginal product and the input price across inputs. Specifically, we utilize the materials as the input where firms have no monopsony power.[4]

We 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 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

[4] Any monopsony power in materials would lead us to understate the levels of markdowns on labor.

allow for factor augmenting technological change, but they require alternative assumptions. However, 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 for 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 of firms exercising market power against labor in both China and India, and in China we find cooperation amongst firms. The impact on labor's share is sizable amounting to nearly 15 percentage points in India and 10 percentage points in China at the beginning of our samples (1999). Cooperative exercise of market power has no impact on labor's share in India and decreases labor's share by only 0.5 percentage point in China. Finally, market shares somewhat declined on average in both countries, so the importance of monopsony power for market shares is about half as large by the end of the samples, 2007 in China and 2011 in India. When we add in the impact of market power in the output market and setting of markups, the total impact on labor's share in India was as large as 17 percentage points. For comparison, these impacts are much larger than the reported time series 5 percent decline in the global labor's share over 35 years in Karabarbounis and Neiman (2013).

The overall impacts on wages are also quantitatively important. In India, the impact of cooperative monopsony is negligible, but the exercise of monopsony power by individual firms in general lowers wages by about 5 percent. In China, the total effect of monopsony power is to lower wages by about 4 percent, with about 1.5 percentage points coming from cooperative monopsony power. The burden of monopsony power is not distributed uniformly, however. For example, the median impact in India is just 3.5 percent, but 10 percent of labor markets have wages lowered by at least 10 percent. In environments where manufacturing wages are already low, these impacts are therefore substantial.

This study contributes to several existing literatures. The paper is most closely related to BKL, who also study the cooperation of firms in industrial clusters in China. BKL focus on product market competition, finding strong results of cooperation, especially within SEZs. We develop analogous empirical methods to quantify the effects of labor monopsony. The further validation exercises and null results that we find for India only strengthen the Chinese results, since it shows the ability of the screen to distinguish between cooperation and noncooperation empirically. Moreover, we show that the results are robust to different measures of markups. We also show that the product market screen is robust to the inclusion of labor market power.

The idea that firms might use market power and even collaborate to lower wages is quite old, dating most famously to Marx (1867) but also the earlier work of Smith (1776) and Malthus (1798), who wrote of guilds suppressing the wages of apprentices and landlords against agricultural workers. The case of monopsony in the market for agricultural labor has been well-studied in the development literature, although much of it is theory (Binswanger and Mark R. Rosenzweig, 1984; Braverman and Stiglitz, 1982, 1986). As mentioned, an existing empirical literature in the United States (Lambson and Ransom, 2011; Ransom, 1993) again focuses on identifying monopsony in particular industries. 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.

In the recent macro literature, monopsony power is the focus of several concurrent studies focusing on the United States, including Card et al. (2018), Gouin-Bonenfant (2018) ,Lamadon, Mogstad and Setzler (2017), and Berger, Herkenhoff and Mongey (2018). The first three examine the sharing of rents in matching or search labor markets. We study the exertion of classical market power in a classical labor market, where workers have no market power of their own. Berger, Herkenhoff and Mongey (2018) study a similar labor market, but they use mergers as their identifying approach. Relative to this literature, our focus on developing countries is unique.

Several recent studies have focused on estimating the impact of competition on firm's market power using the same plant-level manufacturing data in India. Asturias, Manuel Garcia-Santana and Ramos (2015) show that the the highway system in India led to increased competition among manufacturing firms, lower markups, and welfare gains. In contrast, Galle (2016) shows that pro-competitive reforms in India led to a decrease in convergence because capital constraints were binding for firms. In related theoretical work, Itskhoki and Moll (2017) show that the suppression of wages can be welfare improving, when firms face financial constraints. Empirically, we are the first to estimate the suppression of wages in a developing country, but our analysis is purely positive. We cannot evaluate the welfare implications of the wage markdowns we estimate.

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

## I. Model

In this section, we present the model of the exercise of independent and cooperative firm market power in the output and factor markets.

### *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 $y_{nki}$. Output can be costlessly traded across locations, so firm $n$ in industry $i$ and location $k$ faces an inverse demand function that is independent of its location $k$. The price a firm can sell at depends on its own output and the output of other firms. Following BKL, we assume the following functional form for this inverse demand:

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

where $P$ is the aggregate price level, and $D_i$ is an exogenous, industry-level demand parameter. Industry output $Y_i$ is given by:

$$Y_i = \left(\sum_{k=1}^{K}\sum_{n=1}^{N_{ki}} y_{nki}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

This demand system can be derived from nested constant elasticity of substitution (CES) preferences where goods within sectors and across sectors have different elasticities of substitution. A critical assumption is $\sigma > \gamma$, which amounts to assuming that goods are closer substitutes to other goods within their industry than they are to goods in other industries.

Our strong assumptions on demand allow us to be relatively flexible in specifying production technologies. Production uses inputs $\{x_{mnki}\}$, where $m = 1...M$ according to a production function:

$$y_{nki} = F_i(x_{1nki}, ..., x_{Mnki}; Z_{nki}) \tag{3}$$

where $Z_{nki}$ is a set of firm-level characteristics, including productivity but also any other potential firm or location-specific factors that might affect the level or shape of technology.

Factor markets are segmented by industry and location, and factor prices are therefore given by an exogenous inverse supply function such that the market supply $X_{mki}$ and price $q_{mki}$ of factor $m$ are both location $k$ and industry $i$-specific:

$$q_{mki} = G_{mi}\left(X_{mki}\right), \tag{4}$$

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

$$X_{mki} = \sum_{n=1}^{N_{ki}} x_{mnki}. \tag{5}$$

### B. *Cooperative Behavior*

The objective of each firm is to maximize the sum of its own profit and (potentially) the weighted costs and revenues of other firms in a group $S_{nki}$.[5] In particular, $\kappa \in [0,1]$ measures the weight put on the other firms' revenues, while $\kappa_m \in [0,1]$ is the weight put on the costs paid by those firms in factor market $m$. Specifically, each firm maximizes:

$$\max_{\{y_{nki},\{x_{mnki}\}\}} p_{nki}y_{nki} + \kappa \sum_{l\in S_{nki}} p_{nki}y_{lki} - \sum_{m=1}^{M} q_{mki}\left[x_{mnki} + \kappa_m \sum_{l\in S_{nki}} x_{mlki}\right] \tag{6}$$

subject to:

$$y_{nki} = F_i(x_{1nki}, ..., x_{Mnki}; Z_{nki})$$
$$p_{nki} = P\left(\frac{y_{nki}}{Y_i}\right)^{-1/\sigma}\left(\frac{Y_i}{D_i}\right)^{-1/\gamma}$$
$$q_{mki} = G_{mi}\left(X_{mki}\right).$$

At the extremes, this objective function could describe firms operating independently ($\kappa = 0$ and $\forall m, \kappa_m = 0$), or as members of perfect cartels ($\kappa = 1$ and $\forall m, \kappa_m = 1$), who cooperate on output and all input markets. In general, the parameters $\kappa$ and $\kappa_m$ stand in for all parameters capturing effective cooperation between a firm and the members of $S_{nki}$ in the output ($\kappa$) and factor markets ($\kappa_m$). We do not interpret these weights as necessarily reflecting the preferences of the firm owners. They may represent the outcome of a more complex system to maintain cooperation among a set of firms, which may differ for output and the various factor markets. That is, firms may effectively weight revenues and costs differently because they have different incentives or ability to cooperate in either

[5] Firm $n$ is not a member of $S_{nki}$.

increasing revenues or reducing costs or different abilities to redistribute the overall gains from these activities. Some groups of firms may only cooperate on output markets. Others may only cooperate on input markets, and only for certain inputs.

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, but they also reduce the price of the other firms in their industry, including the members of $S_{nki}$ that appear in their objective function. Similarly, by choosing to use more of an input $m$, firms internalize the effect of higher input prices on themselves, and, with a weight $\kappa_m$, on firms in $S_{nki}$.

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

$$p_{nki} + \frac{\partial p_{nki}}{\partial y_{nki}} y_{nki} + \kappa \sum_{l \in S_{nki}} \frac{\partial p_{lki}}{\partial y_{nki}} y_{lki} = \lambda_{nki} \tag{7}$$

$$q_{mki} + \frac{\partial q_{mki}}{\partial x_{mnki}} x_{mnki} + \kappa_m \sum_{l \in S_{nki}} \frac{\partial q_{mki}}{\partial x_{mnki}} x_{mlki} = \lambda_{nki} \frac{\partial F_i}{\partial x_{mnki}} \tag{8}$$

Notice that equations (7) and (8) can be rewritten, respectively, as:

$$\frac{\lambda_{nki}}{p_{nki}} = 1 + \frac{\partial \log(p_{nki})}{\partial \log(y_{nki})} + \kappa \sum_{l \in S_{nki}} \frac{\partial \log(p_{lki})}{\partial \log(y_{nki})} \frac{p_{lki} y_{lki}}{p_{nki} y_{nki}} \tag{9}$$

$$\lambda_{nki} \frac{y_{nki} \frac{\partial \log(F_i)}{\partial \log(x_{mnki})}}{q_{mki} x_{mnki}} = 1 + \frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})} \left( 1 + \kappa_m \sum_{l \in S_{nki}} \frac{x_{mlki}}{x_{mnki}} \right) \tag{10}$$

We assume the existence of a factor for which all firms are price takers.[6] We denote this

[6] Empirically, we will use materials.

input with the index 0. That is, we assume:

$$\forall n, \frac{\partial \log(q_{0ki})}{\partial \log(x_{0nki})} = 0 \tag{11}$$

We define a markup $\mu^0_{nki}$ 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:

$$\frac{\frac{q_{0ki}x_{0nki}}{p_{nki}y_{nki}}}{\frac{\partial \log(F_i)}{\partial \log(x_{0nki})}} = \frac{1}{\mu^0_{nki}} = 1 + \frac{\partial \log(p_{nki})}{\partial \log(y_{nki})} + \kappa \sum_{l \in S_{nki}} \frac{\partial \log(p_{lki})}{\partial \log(y_{nki})} \frac{p_{lki}y_{lki}}{p_{nki}y_{nki}} \tag{12}$$

The left hand term is (the reciprocal of) the familiar expression derived in de Loecker and Warzynski (2012). For the elastically supplied input 0, dividing the output elasticity with respect to input 0 by the expenditure share of revenues of input 0 gives the markup, which we denote $\mu^0_{nki}$. 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 this same measure across inputs provides a way of inferring monopsony power in those other inputs. Combining equations (9) and (10) for any input $m$ implies:

$$\mu^m_{nki} \equiv \frac{\frac{\partial \log(F_i)}{\partial \log(x_{mnki})}}{\frac{q_{mki}x_{mnki}}{p_{nki}y_{nki}}} = \frac{1 + \frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})}\left(1 + \kappa_m \sum_{l \in S_{nki}} \frac{x_{mlki}}{x_{mnki}}\right)}{1 + \frac{\partial \log(p_{nki})}{\partial \log(y_{nki})} + \kappa \sum_{l \in S_{nki}} \frac{\partial \log(p_{lki})}{\partial \log(y_{nki})} \frac{p_{lki}y_{lki}}{p_{nki}y_{nki}}} \tag{13}$$

The term $\mu^m_{nki}$ is the markup as measured with the de Loecker and Warzynski (2012) method when applying the elasticity and factor share of the input $m$. This now has two components. The distortion to firm production choices appears in the denominator of the right hand side, and is the same for all inputs. The distortion due to monopsony power in input market $m$ is in the numerator of the right hand side, and varies by input. Making use of the special case of input 0, where we assume that monopsony power is absent, we note that we can isolate the monopsony power of input $m$ by writing:

$$\forall m, \frac{\mu^m_{nki}}{\mu^0_{nki}} = 1 + \frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})} \left(1 + \kappa_m \sum_{l \in S_{nki}} \frac{x_{mlki}}{x_{mnki}}\right) \tag{14}$$

Because, in general, the firm may not be price-taking for input $m$, $\mu^m_{nki}$ could exceed one for multiple reasons: market power in the output market, monopsonistic market power in the input market, or some combination. To isolate the latter factor, we can measure monopsony power in the market for input $m$ by comparing the de Loecker and Warzynski (2012) markup measure across inputs. In the absence of monopsony power, using any input implies the same measured markup. Therefore, when one input is known to exhibit no market power that allows us to measure monopsony power in the other inputs. 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 $G_{mi}$:

$$G_{mi}\left(X_{mki}\right) = A_{mki}\left(X_{mki}\right)^{\frac{1}{\phi_m}} \tag{15}$$

where $A_{mki}$ is an exogenous constant and $\phi_m$ measures the elasticity of supply. Then:

$$\frac{\partial \log(q_{mki})}{\partial \log(x_{mnki})} = \frac{1}{\phi_m} s^m_{nki} \tag{16}$$

which we can substitute into equation (14) to yield:

$$\frac{\mu^m_{nki}}{\mu^0_{nki}} = 1 + \frac{(1 - \kappa_m)}{\phi_m} s^m_{nki} + \frac{\kappa_m}{\phi_m} \sum_{l \in S_{nki} \cup \{n\}} s^m_{lki} \tag{17}$$

where we have defined $s^m_{lki}$ as the input share of firm $n$ in the location $k$- and industry

$i$-segmented market for input $m$:

$$(18) \qquad s_{nki}^{m} = \frac{q_{mki}x_{mnki}}{\sum_{l} q_{mki}x_{mlki}}.$$

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 (i.e., $\kappa = 0$) or their markdowns (i.e., $\kappa_m = 0$), the measured markups and markdowns will depend on the relevant share of their own firm. However, if they are perfectly cooperating, they will depend on the total relevant share of all the firms they internalize. Thus, if the firms are perfectly jointly cooperating, they will charge either the same markup (in the case of product market cooperation) or the same markdown (in the case of factor market cooperation), and partial cooperation will lower the variation in markups and markdowns.

Likewise, we can use the functional form of output demand to generate a corresponding equation to estimate monopoly power. In particular, using (1) and aggregate industry-level output in equation (2), we can write the equations for markups in terms of market shares as:

$$(19) \qquad \frac{1}{\mu_{nki}^{0}} = 1 - \frac{1}{\sigma} - (1-\kappa)\left(\frac{1}{\gamma} - \frac{1}{\sigma}\right) s_{nki} - \kappa \left(\frac{1}{\gamma} - \frac{1}{\sigma}\right) \sum_{l \in S_{nki} \cup \{n\}} s_{lki}$$

where $s_{nki}$ are the firms' shares in output markets. As in BKL, this gives a linear equation to evaluate monopoly power that firms exert in output markets.

### *C. Calculating Aggregate Labor's Share*

We have defined things generally in terms of inputs indexed by $m$, but we focus here on labor, which we denote with script $L$. Moreover, we denote intermediates with the superscript $M$. The labor share as a fraction of value added in this economy is defined as:

$$\eta_L = \frac{\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} q_{Lnki} x_{Lnki}}{\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} (p_{nki} y_{nki} - q_{Mnki} x_{Mnki})} \tag{20}$$

Define the labor share of a given firm in the national labor pool as:

$$\omega^L_{nki} = \frac{q_{Lnki} x_{Lnki}}{\sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} q_{Lnki} x_{Lnki}} \tag{21}$$

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:

$$\frac{1}{\eta_L} = \sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \frac{p_{nki} y_{nki}}{q_{Lki} x_{Lnki}} \omega^L_{nki} - \sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \frac{q_{Mki} x_{Mnki}}{q_{Lki} x_{Lnki}} \omega^L_{nki} \tag{22}$$

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

$$\mu^L_{nki} \equiv \frac{\theta^L_{nki}}{\frac{q_{Lki} x_{Lnki}}{p_{nki} y_{nki}}}, \qquad \mu^M_{nki} \equiv \frac{\theta^M_{nki}}{\frac{q_{Mki} x_{Mnki}}{p_{nki} y_{nki}}} \tag{23}$$

where for any input $m$,

$$\theta^m_{nki} \equiv \frac{\partial \log(F_i)}{\partial \log(x_{mnki})}. \tag{24}$$

These imply that:

$$\frac{p_{nki} y_{nki}}{q_{Lki} x_{Lnki}} = \frac{\mu^L_{nki}}{\theta^L_{nki}}, \qquad \frac{p_{nki} y_{nki}}{q_{Mki} x_{Mnki}} = \frac{\mu^M_{nki}}{\theta^M_{nki}} \implies \frac{q_{Mki} x_{Mnki}}{q_{Lki} x_{Lnki}} = \frac{\mu^L_{nki} \theta^M_{nki}}{\mu^M_{nki} \theta^L_{nki}} \tag{25}$$

Finally, this can be substituted into equation (22) to get:

$$\frac{1}{\eta_L} = \sum_i \sum_{k=1}^{K} \sum_{n=1}^{N_{ki}} \left[ \frac{\mu_{nki}^L}{\mu_{nki}^M} \frac{\mu_{nki}^M - \theta_{nki}^M}{\theta_{nki}^L} \omega_{nki}^L \right] \tag{26}$$

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, setting $\frac{\mu_{nki}^L}{\mu_{nki}^M} = 1$ gives labor's share when monopsony power has been eliminated. Keeping this ratio constant, but adjusting $\mu_{nki}^M = 1$ yields the impact of market power in the product market on labor's share.

## II. 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 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).[7] It contains the most

[7]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 screen would only operate through our estimates of market share and should therefore be minimal.

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 2009, 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.[8] 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. The "parent id code", which we use to identify affiliated firms, is only available for the year 2004, but we assume that ownership is time invariant.

For India, we do not include useful location and ownership in a single dataset. Instead, 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 industry and state. 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

[8]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.

of depreciation. As with China, we focus only on the manufacturing sector and focus on 4-digit manufacturing industries.

### *B. Measuring Markups and Markdowns*

In order to implement our tests in Section I, we need measures of markups. These markups will be used directly in our product market screen, and as part of our measurement of labor markdowns in our labor market screen. 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 $\alpha_{i,t}^M$:

$$\mu_{i,t}^M = \frac{\theta_{i,t}^M}{\alpha_{i,t}^M}. \tag{27}$$

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 DLW 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 is 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. Since this is the standard way of estimating markups (e.g., de Loecker and Warzynski (2012), Edmond, Midrigan and Xu (2015), de Loecker et al. (2016), and BKL), we present this as one measure, but we allow for several alternatives. We label this markup method "DLW", since it most closely follows their implementation.

Our second method uses the markup formula in equation (27), 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 poses no problem for us. Indeed, for some purposes, we can allow this elasticity to remain an unknown.[9] However, we instead choose $\theta$ so that our markups equal a reasonable average value of 1.2. We refer to this second markup measure as "CD", which stands for Cobb-Douglas.

Our third 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 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. The precise formula we use is:

[9] In this case, our measure of the inverse markup in equation (29) of the next section would simply be the share of materials normalized by a scalar. Omitting the unknown scalar, we lose estimates of demand elasticities in our demand system, but we retain our estimates of $\kappa$.

$$\mu_{i,t}^{M} = \frac{sales}{costs} = \frac{py}{q_K x_K + q_L x_L + q_M x_M}. \tag{28}$$

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 this measure of markups is less appropriate in the presence of markdowns 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).

As in the CD case, we have an average markup of 1.2 in mind as a target and assign a value of $q_K = 0.12$. We view this as reasonable rental rate on capital, since it includes both depreciation and a reasonably high return to capital-poor, but rapidly-growing, countries like China and India.. This yields an average markup of 1.16 in China and 1.22 in India. We label this third markup measure as "CRS", which stands for the constant returns to scale assumption.

In each case, markups are clearly measured with substantial error. We therefore trim 3 percent in both sides of the tails of each industry.

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.[10] Market shares are constructed at the national level for 4-digit industries for most of our analyses. The narrow industry classification best reflects the horizontal model of competition, and the ownership validation results confirm this.[11] Nevertheless, the market shares tend to be quite small at the firm level, especially in the Indian ASI. Again, it is clear that the typical firm in Prowess is substantially larger than the typical plant in ASI. Since we use Prowess to test for cooperation among jointly owned firms and

[10]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.

[11]We also find similar results in China for the narrowest industry classification. See BKL.

ASI to test for local cluster level cooperation we present the average market shares at these levels in each respective data set. 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 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 monopsonistic cooperation, 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 (27). We measure the labor-based markup again using the CD approach, assuming a constant $\theta^L$. However, since we lack a solid target for markdowns (analogous to our the markup target used to assign $\theta^L$), we instead calibrate this elasticity by using the fact that absent market power in the factor market, the markdown should be one.[12] This requires trimming the outliers in the sample in terms of markdown, and we trim the 3% tails based on the overall markdown. Notice in the CD case, that the markdown becomes materials payments over labor payments multiplied by a constant equaling the ratio $\theta^L/\theta^M$.

[12] Again, this normalization is only necessary for interpreting the quantitative impact of markdowns on wages, but not for the estimate of $\kappa_L$.

### C. Empirical Estimation of Market Power

Our empirical tests draw directly from the optimization relationships derived in Section I. 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 (19), empirically implemented as:

$$\frac{1}{\mu^M_{nit}} = \Gamma_t + \alpha_{ni} + \beta_1 s_{nit} + \beta_2 \sum_{m \in S} s_{mit} + \varepsilon_{nit} \tag{29}$$

Comparing, we see that the estimation adds time dummies $\Gamma_t$, firm-specific fixed effects, $\alpha_{ni}$ (which can partially account for firm-specific demand elasticities, see BKL), and an error term $\varepsilon_{nit}$ that stems from either measurement error or unanticipated shocks. Note that we can easily solve for the extent of product market cooperation using the formula, $\kappa = \beta_2 / (\beta_1 + \beta_2)$. In principle, using these coefficients together with the average level of markups, we can also solve easily for the values of $\sigma$ and $\gamma$ as well. This is precisely the test proposed and applied by BKL, so there is nothing new here except to show that it is robust to the possible presence of monopsony power and even monopsonistic cooperation, 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:

$$\frac{\mu^L_{nkit}}{\mu^M_{nkit}} = \Gamma_t + \alpha_{ni} + \beta_{1,L} s^L_{nkit} + \beta_{2,L} \sum_{l \in S_{nkit} \cup \{n\}} s^L_{lkit} + \varepsilon_{nkit} \tag{30}$$

and the extent of monopsonistic cooperation in the labor market can analogously be solved as $\kappa_L = \beta_{2,L} / (\beta_{1,L} + \beta_{2,L})$.[13] A more direct equation would utilize the fact that the markdown equals unity in the absence of any market power (i.e., labor market share of zero

[13] Again, in principle we could solve for the values of the input supply elasticity $\phi_L$, but this will not be practically feasible, as we explain below.

and no labor market cooperation). However, in practice there is considerable measurement error in the estimation of markups themselves. Since these markups are in the denominator, the convex relationship of $1/\mu_{nit}$ leads to markdowns measures that are much larger than one on average. Thus, the level of markdowns (captured by the intercepts and fixed effects) will be less informative than the increase in markdowns coming from market power (captured by the estimates of $\beta_{1,L}$ and $\beta_{2,L}$).

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 by instead using the revenue share of a firm within the labor market, $s^*_{nki} = \frac{p_{nki}y_{nki}}{\sum\limits_{l} p_{lki}y_{lki}}$.

Comparing the two regression equations, (29) and (30), the precise regressions clearly differ, but notice that the identification and intuition behind both the product market and factor market screens are analogous. If firms' markups comove with their own market share over time, then this looks like independent exercise of market power. If, however, firms' markups comove together and in synchrony with the total market share of a set of firms, we infer that they are effectively using this combined market power to manipulate markups. Similarly, if we see markdowns moving independently with the firm's share in the labor market over time, we attribute this to the independent exercise of monopsony power. Alternatively, if we see it comoving together with the total importance of the firms in the factor market, we infer that they are cooperating to utilize their combined purchasing power to manipulate markdowns, at least effectively.

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). This underscores a strong reason for adding firm-specific fixed effects in our regression equation (30). Again, examining equation (30) further, that we will only attribute the component of this markdown that covaries with labor market share as an exercise of labor market power.

Another possible interpretation of this "wedge" might be that it reflects labor adjustment costs. Labor adjustment costs themselves are typically a blackbox way of capturing a wedge, but a wedge with particular dynamics. 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 of labor is lower in the short-run than in the long run. The ACF 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.[14]

Nevertheless, 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 (30) using a longer four-year difference. Changes over four years are less likely to reflect short-term adjustments costs.

A final 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 provinces

[14]As noted, adjustment costs are assumptions of labor wedges with particular dynamic properties. In principle, these properties have testable implications: the wedge of additional workers is temporary with adjustment costs, while it is permanent in the case of the static monopsony wedges we assume. In practice, it is difficult to distinguish the two.

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.

## III. 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. We derive standard errors on $\kappa$ and $\kappa_L$ using the delta method. 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.

### *A. Monopsony in the Local Labor Market*

We present the results for exertion of monopsony power in labor markets using the estimation in equation (30). We run the tests using all three markdown measures, and the full set of manufacturing firms. These results are presented in Table 4. 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. Nevertheless, 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.

In China, both the coefficients on own labor market share and cluster labor market share are significant, while in India only the own labor market share coefficients are significant. In both countries, however, the coefficients on the firm's labor market share are many times larger than the coefficient on the cluster's labor market share.

For China, this yields a relatively small, though statistically significant, measure of $\kappa_L$, ranging from about 0.020 to 0.130 depending on the definition of markups and labor markets. Again, these levels are reasonably robust across the different specifications although somewhat weaker the more broadly we define labor markets. For India, the estimates for $\kappa_L$ are statistically insignificant and negligible in magnitude. Thus, we see no evidence of cooperative monopsony in the Indian labor market, and evidence of only mild cooperation in China.

Focusing on the implied elasticity of supply parameter, $\phi$, 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 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, there is mild cooperation among firms in China in the exercise of this monopsony power. Finally, the implied labor supply elasticities are reasonable.

As discussed in Section II.C, one possible interpretation of these results is that the measures reflect adjustment costs on labor. To evaluate this, we look at four-year differences in the data, and these results are presented in Table 5. Naturally, this involves dropping much more data, so the sample sizes are substantially smaller. Nevertheless, the results are extremely 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, while the cluster's labor market share is only significant in China. The magnitudes of the coefficients are also quite similar. The implied estimates of $\kappa_L$ are also quite similar: small and statistically insignificant in India, while significant and ranging from 0.028 to 0.118 in China. Moreover, the implied labor supply elasticities are similar. 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 and somewhat larger $\kappa_L$ 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 (29). We also look for the cooperative exercise of market power in the product market among firms in the same location and 4-digit industry.

BKL run these regressions for China using the CIE data. 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. Their estimates of $\beta_1$ and $\beta_2$ were 0.099 and 0.040, and were both highly significant. These implied a significant value of $\kappa = 0.29$ for China, which was again significant.

We present similar results for India. BKL also validated the cooperative aspect of the test, using plants that are affiliates of the same parent corporation. Although our ASI data for India do not contain information on owernship, we present a similar validation exercise for India which is presented in the Appendix.[15] The robustness of these results also acts as a validation of our various markup measures. While we find evidence that market share is

[15]The ASI data for India do not have data on ownership, but the appendix presents results using an alternative firm data source, Prowess. Moreover, this acts as a Prowess does not allow us to do local labor market cooperation because the data are at the level of the firm and do not contain data on the location of plants.

important for markups in India, we find no evidence of product market cooperation among plants in India.

Table 6 presents the overall results using 4-digit industries as a product market definition for India. For all three markup measures, the coefficients on own share are large and statistically significant at a one percent level. In contrast, the coefficient on local cluster (i.e., 4-digit industry by district) market share is relatively small and insignificant, indicating no local cooperation among firms. Moreover, the $\kappa$ estimates are small and significant.[16]

We note, however, that relative to China, the estimates of $\beta_1$ are substantially larger. This indicates that Indian firms can exercise substantial market power on their own, independent of cooperation. This may be the result of lower demand elasticities (compare the coefficient on market share with Equation (19) 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 $\beta_1$ and market share, is what drives the additional markup, and those are quite similar regardless of how we define markets.[17]

In sum, while BKL found evidence of some market power exertion in product markets in China, and even cooperative market power exertion, in India we find no evidence of cooperative market power exertion but much stronger evidence of the ability to independently

[16]The fact that we find both null results for local cooperation in the overall sample, but positive results in the validation exercise, and intermediate results for China in BKL is further evidence that the test is able to discern cooperation from noncooperation.

[17]An element of systematic measurement error in market shares, however, might in principle also distort our measures of cooperation, however, so we examined this more closely. We did so in several ways. First, we note that the coefficients in the appendix for Prowess, which is disproportionately large public firms, are much smaller and comparable to those in China. These firms are more likely to have national markets. Second, we defined product markets at the state level for the ASI data. This leads to smaller coefficients, on the order of those in Prowess, but does not lead to any significance of the cluster market share or to any significant $\kappa$ estimates. Second, we try to isolate this effect by dividing the sample of industries into three terciles of tradability: high tradable, medium tradable, and less tradable. We measure tradability using the Hirschmann-Herfindahl index, and also some measure of trade's importance using global international trade flows as a proxy. In both cases, the estimated $\beta_1$ coefficients themselves are more similar to the smaller coefficients found in Prowess for the highly tradable industries, but the estimates of $\beta_2$ and $\kappa$ remain insignificant. This last result is even more striking since one might surmise that a higher level of industrial concentration enables easier cooperation among firms. Indeed, BKL found evidence of this pattern in China. In sum, we find little to no evidence of cooperation in India.

exert market power.

### C. *Aggregate Impact of Monopsony on 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 4-6 imply estimates for wages across all years.[18] We then look at the implications for market concentration on wage levels themselves. We run three counterfactuals: (i) no cooperative monopsony in labor market ($\kappa_L = 0$), (ii) no monopsony power at all in the labor market ($\kappa_L = s^L = 0$), (iii) no monopsony power in the labor market and no exercise of market power in the product market ($\kappa_L = s^L = s = 0$). (For India, $\kappa_L$ was estimated to be small and statistically insignificant, so we omit the first counterfactual.)

Table 7 presents the average relative wage gains from these counterfactuals as a fraction of actual wages. We see that in both countries, the labor market power drives the results. In China, wages would be up to 4.1 percentage points higher, while in India, they would up to 5.3 percentage points higher. The product market is relatively small in both countries: negligible in China, while contributing up to 0.6 percentage points in India. Going across the columns, the results are remarkably robust, regardless of which formula we use to estimate markups.

Table 8 examines the variability of these wage gains across labor markets. Wage gains in the median labor market are small, roughly 2.5 percent in China and 3.5 percent in India, but they are substantial in the 10 percent of markets where labor market concentration is highest, about 9 percent of wages in China and 10 percent in India. 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)

[18] We have ignored the scale of markups measures in our markdown equation, since markdowns only use the ratio, but we need to scale them for these estimates. We again normalize the benchmark markup to 1.20, consistent with our estimation assumption for the CD and CRS markups.

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 India showing a substantial decline before 2004, and an increase afterwards, while China is relatively flat until 2004, when it begins to decline.

Given the estimates above, we follow the approach into Section I.C in order to estimate the quantitative importance of our monopsony and monopoly power estimates for labor's share. 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, although we find evidence of cooperation in the product market, the coefficient and market shares together are too small to make any visual impact on the the labor's share. We therefore only present labor market monopsony counterfactuals. The dashed line sets $\kappa_L = 0$, and therefore asks what would labor's share be if firms did not cooperate in the labor market. It leads to a small gain in labor's share of about 0.5 percentage point throughout the period. If, however, firms had no market power at all in the labor market, i.e., $s^L = 0$, akin to price takers in wages, labor's share would have been about 10 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.

In India, we found no evidence of cooperative firm behavior. We therefore omit those separate counterfactuals from the figure. We did, however, find strong market power in product markets so the India panel instead breaks out the results by monopsony and monopoly power. The dashed line counterfactual shows that without any monopsony power, labor's share in India would have been as much 13 percentage points higher at the beginning of the sample, although the impacts falls to about 6 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 as high as 4 percentage point in 2000 and falls to just below 2 percentage points by 2011. Without either source of concentration driven market power, labor's share would have been as high as 17 percentage points higher (in 2000), and falling to about 8 percentage points higher 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.

## IV. Conclusion

We have developed a simple empirical screen for quantifying the impact of market power in the labor market, including that resulting from cooperative markdown behavior among subsets of firms. 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.

The results are important in validating previous work as well. First, we showed that the both the product market and labor market screens are robust to various ways of measuring markups. Second, the product market test has now been validated in two countries. In contrast to China, India exhibited no local cooperation in the product markup, however. This is further evidence that the labor market screen is nuanced in finding results of firm cooperation.

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Figure 1. Concentration measured using the Herfindahl Index

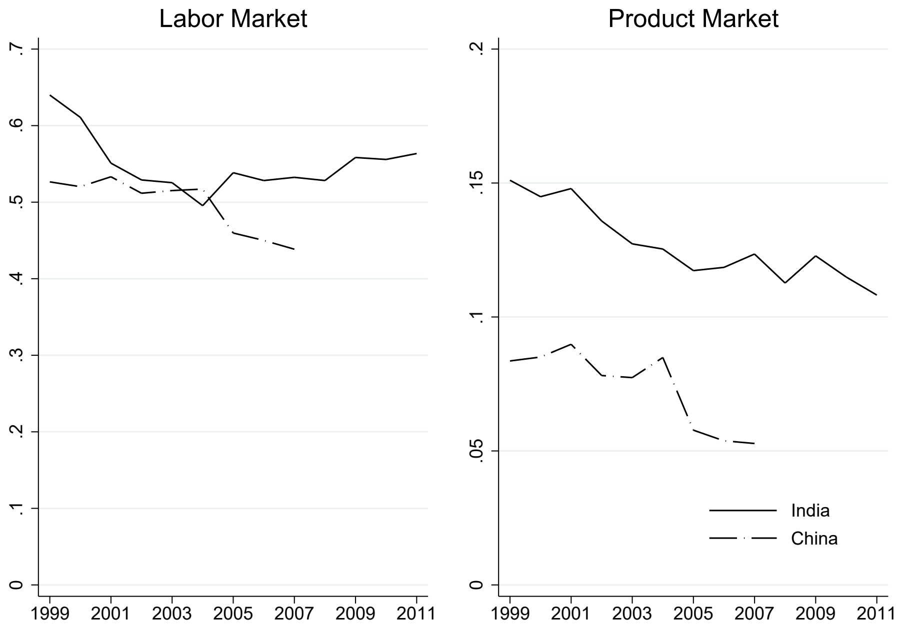
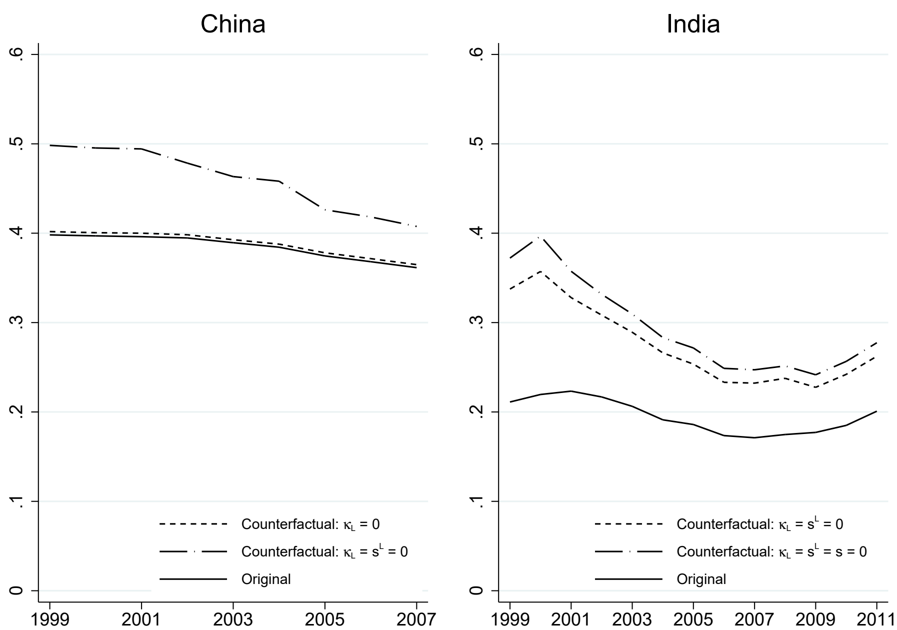



Figure 2. Labor Share Counterfactuals




Notes: Computation is based on Markup(CD). The industry is defined at the 4-digit level.

Table 1—Key Summary Statistics of Data

| | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| *Panel A: China CIE* | | | | | |
| Markup (DLW) | 1.26 | 1.24 | 0.19 | 0.64 | 4 |
| Markup (CD) | 1.19 | 1.17 | 0.19 | 0.89 | 33 |
| Markup (CRS) | 1.15 | 1.14 | 0.17 | 0.01 | 4 |
| Firm Share | 0.003 | 0.0006 | 0.02 | 0 | 1 |
| Cluster Share (Province) | 0.14 | 0.10 | 0.14 | 0 | 1 |
| Cluster Share (City) | 0.04 | 0.01 | 0.06 | 0 | 1 |
| Real Capital per Firm (000s Rs) | 303.4 | 46 | 3368 | 0.01 | 753064 |
| Real Materials per Firm (000s Rs) | 647.8 | 158 | 5176 | 0.01 | 849709 |
| Real Output per Firm (000s Rs) | 881.2 | 223 | 6879 | 0.02 | 1230552 |
| Workers per Firm | 295 | 120 | 1031 | 10 | 166857 |
| No. of firm-year obs | | | 1168944 | | |
| *Panel B: India ASI* | | | | | |
| Markup (DLW) | 1.44 | 1.29 | 2.90 | 0 | 1380 |
| Markup (CD) | 1.08 | 0.96 | 1.60 | 0.14 | 729 |
| Markup (CRS) | 1.19 | 1.16 | 0.33 | 0 | 6 |
| Firm Share | 0.005 | 0.0004 | 0.02 | 0 | 1 |
| Cluster Share (State) | 0.10 | 0.06 | 0.12 | 0 | 1 |
| Cluster Share (District) | 0.03 | 0.01 | 0.08 | 0 | 1 |
| Real Capital per Firm (000s Rs) | 1353 | 43 | 18357 | 0 | 3402507 |
| Real Materials per Firm (000s Rs) | 3072 | 225 | 48572 | 0 | 12858844 |
| Real Output per Firm (000s Rs) | 4209 | 292 | 65108 | 0.01 | 18601728 |
| Workers per Firm | 191 | 42 | 805 | 1 | 61869 |
| No. of firm-year obs | | | 340499 | | |
| *Panel C: India Prowess* | | | | | |
| Markup (DLW) | 1.70 | 1.49 | 0.90 | 0 | 75 |
| Markup (CD) | 1.17 | 1.06 | 0.86 | 0.18 | 67 |
| Markup (CRS) | 1.26 | 1.24 | 0.37 | 0 | 4 |
| Firm Share | 0.05 | 0.01 | 0.11 | 0 | 1 |
| Ownership Share | 0.07 | 0.02 | 0.13 | 0 | 1 |
| Real Capital per Firm (000s Rs) | 896365 | 149455 | 8898485 | 53 | 531795725 |
| Real Materials per Firm (000s Rs) | 833477 | 155148 | 9440649 | 22 | 670275497 |
| Real Output per Firm (000s Rs) | 1283072 | 247960 | 12052021 | 26 | 781928311 |
| No. of firm-year obs | | | 27693 | | |

Notes: Market shares are computed using 4-digit industries. Capital, materials, and output are in thousand Rupees/RMB (in real value). The table trims the observations with all markup measures that are above and below the 3rd and 97th percentiles.

Table 2—Cross-correlation Matrix across Three Markup Estimates

| | Markup (DLW) | Markup (CD) |
|---|---|---|
| *Panel A: China CIE* | | |
| Markup (CD) | 0.76 | |
| Markup (CRS) | 0.62 | 0.59 |
| *Panel B: India ASI* | | |
| Markup (CD) | 0.78 | |
| Markup (CRS) | 0.56 | 0.68 |
| *Panel C: India Prowess* | | |
| Markup (CD) | 0.71 | |
| Markup (CRS) | 0.54 | 0.73 |

Notes: The table trims the observations with all markup measures that are above and below the 3rd and 97th percentiles.

Table 3—Summary Statistics of Markdown and Labor Share

| Variable | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| *Panel A: China CIE* | | | | | |
| Markdown (DLW) | 6.14 | 4.04 | 5.87 | 0.03 | 49 |
| Markdown (CD) | 6.65 | 4.34 | 6.45 | 0.01 | 64 |
| Markdown (CRS) | 6.47 | 4.38 | 5.87 | 0.45 | 136 |
| Labor market share (2 digit) | 0.007 | 0.001 | 0.037 | 0 | 1 |
| Labor market share (3 digit) | 0.031 | 0.004 | 0.104 | 0 | 1 |
| Labor market share (4 digit) | 0.064 | 0.008 | 0.167 | 0 | 1 |
| No. of firm-year obs | | | 1120028 | | |
| *Panel B: India ASI* | | | | | |
| Markdown (DLW) | 6.84 | 2.87 | 386.82 | 0.001 | 200612 |
| Markdown (CD) | 6.49 | 3.74 | 7.88 | 0.001 | 84 |
| Markdown (CRS) | 5.00 | 3.05 | 5.79 | 0.32 | 743 |
| Labor market share (2 digit) | 0.024 | 0.002 | 0.089 | 0 | 1 |
| Labor market share (3 digit) | 0.053 | 0.004 | 0.151 | 0 | 1 |
| Labor market share (4 digit) | 0.093 | 0.010 | 0.207 | 0 | 1 |
| No. of firm-year obs | | | 334476 | | |

Notes: The table trims the observations with all markdown measures that are above and below the 3rd and 97th percentiles.

Table 4—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 Trimmed Sample, 1999-2007* | | | | | | | | | |
| Firm's Share | 2.190*** | 0.706*** | 0.383*** | 2.327*** | 0.734*** | 0.396*** | 2.073*** | 0.658*** | 0.356*** |
| | (0.142) | (0.025) | (0.014) | (0.147) | (0.026) | (0.015) | (0.132) | (0.024) | (0.013) |
| Cluster's Share | 0.046*** | 0.048*** | 0.053*** | 0.052*** | 0.058*** | 0.059*** | 0.043*** | 0.047*** | 0.052*** |
| | (0.013) | (0.010) | (0.009) | (0.013) | (0.011) | (0.009) | (0.012) | (0.010) | (0.009) |
| Year FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,005,218 | 1,005,218 | 1,005,218 | 1,005,422 | 1,005,422 | 1,005,422 | 1,005,267 | 1,005,267 | 1,005,267 |
| Adjusted $R^2$ | 0.640 | 0.639 | 0.639 | 0.638 | 0.637 | 0.637 | 0.638 | 0.637 | 0.637 |
| $\kappa_L$ | 0.021*** | 0.064*** | 0.121*** | 0.022*** | 0.074*** | 0.130*** | 0.020*** | 0.067*** | 0.127*** |
| | (0.006) | (0.014) | (0.02) | (0.005) | (0.013) | (0.02) | (0.006) | (0.014) | (0.021) |
| $\phi$ | 0.447*** | 1.325*** | 2.295*** | 0.420*** | 1.261*** | 2.195*** | 0.473*** | 1.418*** | 2.454*** |
| | (0.028) | (0.044) | (0.072) | (0.026) | (0.041) | (0.068) | (0.030) | (0.047) | (0.077) |
| *Panel B: India ASI Trimmed Sample, 1999-2011* | | | | | | | | | |
| Firm's Share | 1.584*** | 0.931*** | 0.641*** | 1.654*** | 0.995*** | 0.704*** | 1.476*** | 0.878*** | 0.616*** |
| | (0.100) | (0.048) | (0.030) | (0.104) | (0.048) | (0.030) | (0.093) | (0.043) | (0.027) |
| Cluster's Share | -0.010 | 0.004 | -0.012 | -0.014 | 0.009 | -0.012 | -0.013 | 0.001 | -0.015 |
| | (0.032) | (0.026) | (0.019) | (0.031) | (0.025) | (0.019) | (0.028) | (0.022) | (0.017) |
| Year FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 287,359 | 287,359 | 287,359 | 297,548 | 297,548 | 297,548 | 295,037 | 295,037 | 295,037 |
| Adjusted $R^2$ | 0.729 | 0.729 | 0.729 | 0.738 | 0.737 | 0.737 | 0.738 | 0.738 | 0.738 |
| $\kappa_L$ | -0.006 | 0.005 | -0.019 | -0.009 | 0.009 | -0.018 | -0.009 | 0.001 | -0.025 |
| | (0.021) | (0.028) | (0.031) | (0.019) | (0.024) | (0.027) | (0.019) | (0.026) | (0.029) |
| $\phi$ | 0.635*** | 1.070*** | 1.590*** | 0.610*** | 0.995*** | 1.446*** | 0.684*** | 1.138*** | 1.666*** |
| | (0.04) | (0.054) | (0.072) | (0.038) | (0.046) | (0.059) | (0.042) | (0.054) | (0.071) |

Notes: Robust standard errors clustered at firm level are in parentheses. Standard errors on $\kappa_L$ and $\phi$ are computed using the delta method. Significance: ***: 1%, **: 5%, *: 10%. We define labor markets at the province level for China and state level for India. A cluster is defined as a group of firms in the same industry locate in the same city/district. 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). All regressions include a constant term.

Table 5—Results about Monopsony Power using Four-year Differences

| | (1) 2-digit | (2) 3-digit | (3) 4-digit | (4) 2-digit | (5) 3-digit | (6) 4-digit | (7) 2-digit | (8) 3-digit | (9) 4-digit |
|---|---|---|---|---|---|---|---|---|---|
| | $\Delta$Markdown (DLW) | | | $\Delta$Markdown (CD) | | | $\Delta$Markdown (CRS) | | |
| *Panel A: Chinese Firms, CIE Trimmed Sample, 1999-2007* | | | | | | | | | |
| $\Delta$Firm's Share | 1.849*** | 0.643*** | 0.343*** | 1.950*** | 0.659*** | 0.348*** | 1.750*** | 0.564*** | 0.303*** |
| | (0.223) | (0.053) | (0.029) | (0.233) | (0.053) | (0.029) | (0.207) | (0.047) | (0.027) |
| $\Delta$Cluster's Share | 0.067** | 0.049** | 0.037* | 0.064** | 0.054** | 0.043** | 0.051** | 0.050** | 0.041** |
| | (0.027) | (0.023) | (0.020) | (0.027) | (0.023) | (0.021) | (0.026) | (0.022) | (0.019) |
| Year FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 163,399 | 163,399 | 163,399 | 163,843 | 163,843 | 163,843 | 163,680 | 163,680 | 163,680 |
| Adjusted $R^2$ | 0.288 | 0.285 | 0.286 | 0.29 | 0.288 | 0.289 | 0.285 | 0.283 | 0.284 |
| $\kappa_L$ | 0.035** | 0.071** | 0.098* | 0.032** | 0.076** | 0.110** | 0.028** | 0.081** | 0.118** |
| | (0.014) | (0.032) | (0.052) | (0.014) | (0.032) | (0.051) | (0.014) | (0.034) | (0.054) |
| $\phi$ | 0.522*** | 1.445*** | 2.627*** | 0.496*** | 1.404*** | 2.556*** | 0.555*** | 1.628*** | 2.910*** |
| | (0.061) | (0.108) | (0.192) | (0.058) | (0.103) | (0.183) | (0.064) | (0.124) | (0.219) |
| *Panel B: Indian Firms, ASI Trimmed Sample, 1999-2011* | | | | | | | | | |
| $\Delta$Firm's Share | 1.561*** | 0.876*** | 0.600*** | 1.644*** | 0.953*** | 0.673*** | 1.423*** | 0.837*** | 0.587*** |
| | (0.181) | (0.080) | (0.054) | (0.189) | (0.083) | (0.056) | (0.167) | (0.075) | (0.051) |
| $\Delta$Cluster's Share | -0.000 | 0.024 | -0.005 | 0.028 | 0.035 | -0.014 | 0.019 | 0.012 | -0.021 |
| | (0.068) | (0.055) | (0.044) | (0.068) | (0.055) | (0.045) | (0.063) | (0.050) | (0.040) |
| Year FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | YES | YES | YES | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 63,419 | 63,419 | 63,419 | 65,438 | 65,438 | 65,438 | 65,068 | 65,068 | 65,068 |
| Adjusted $R^2$ | 0.185 | 0.186 | 0.189 | 0.192 | 0.193 | 0.195 | 0.192 | 0.192 | 0.195 |
| $\kappa_L$ | 0.000 | 0.027 | -0.008 | 0.017 | 0.036 | -0.021 | 0.013 | 0.015 | -0.037 |
| | (0.043) | (0.06) | (0.073) | (0.041) | (0.055) | (0.068) | (0.043) | (0.058) | (0.072) |
| $\phi$ | 0.641*** | 1.112*** | 1.679*** | 0.598*** | 1.012*** | 1.517*** | 0.694*** | 1.178*** | 1.766*** |
| | (0.071) | (0.101) | (0.148) | (0.063) | (0.083) | (0.117) | (0.075) | (0.104) | (0.144) |

Notes: Robust standard errors clustered at firm level are in parentheses. Standard errors on $\kappa_L$ and $\phi$ are computed using the delta method. Significance: ***: 1%, **: 5%, *: 10%. We define labor markets at the province level for China and state level for India. A cluster is defined as a group of firms in the same industry locate in the same city/district. 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). All regressions use the differenced sample and include a constant term.

Table 6—Regression Results about Monopoly Power

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Markup (DLW) | | | Markup (CD) | | | Markup (CRS) | | |
| Firm's Share | -0.633*** | | -0.664*** | -0.483*** | | -0.536*** | -1.039*** | | -1.044*** |
| | (0.073) | | (0.077) | (0.085) | | (0.088) | (0.113) | | (0.115) |
| Region's Share | | -0.086*** | 0.033 | | -0.044* | 0.056** | | -0.180*** | 0.005 |
| | | (0.026) | (0.028) | | (0.024) | (0.025) | | (0.021) | (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 | 287,825 | 287,825 | 287,825 | 297,892 | 297,892 | 297,892 | 295,146 | 295,146 | 295,146 |
| Adjusted $R^2$ | 0.615 | 0.615 | 0.615 | 0.597 | 0.597 | 0.597 | 0.445 | 0.443 | 0.445 |
| $\kappa$ | | | -0.053 | | | -0.116 | | | -0.0035 |
| | | | (0.045) | | | (0.046) | | | (0.021) |

Note: Robust standard errors clustered at firm level are in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Regions are defined at the district level. Market shares are computed using 4-digit industries. Various markup measures are employed, including markup(DLW) (in specifications 1-4), markup(CD) (in specifications 5-8), and markup(CRS) (in specifications 9-12). All regressions include a constant term.

Table 7—Monopsony and monopoly effect on wage

| | Markup(DLW) | Markup(CD) | Markup(CRS) |
|---|---|---|---|
| *Panel A: China CIE* | | | |
| $\kappa_L = 0$ | 0.013 | 0.014 | 0.013 |
| $\kappa_L = s^L = 0$ | 0.039 | 0.041 | 0.036 |
| $\kappa_L = s^L = s = 0$ | 0.041 | 0.042 | 0.038 |
| *Panel B: India ASI* | | | |
| $\kappa_L = s^L = 0$ | 0.049 | 0.051 | 0.044 |
| $\kappa_L = s^L = s = 0$ | 0.053 | 0.052 | 0.050 |

Notes: The estimates are based on 4-digit industry aggregation.

Table 8—Distribution of monopsony effect on wage across labor markets

| | Mean | Median | p75 | p90 |
|---|---|---|---|---|
| *Panel A: China CIE ($\kappa_L = s^L = 0$)* | | | | |
| Markup (DLW) | 0.041 | 0.023 | 0.053 | 0.086 |
| Markup (CD) | 0.044 | 0.025 | 0.056 | 0.091 |
| Markup (CRS) | 0.041 | 0.023 | 0.053 | 0.081 |
| *Panel B: India ASI ($\kappa_L = s^L = 0$)* | | | | |
| Markup (DLW) | 0.050 | 0.034 | 0.067 | 0.090 |
| Markup (CD) | 0.055 | 0.035 | 0.073 | 0.100 |
| Markup (CRS) | 0.047 | 0.031 | 0.064 | 0.092 |

Notes: We define labor markets at the province level for China and state level for India. The estimates are based on 4-digit industry aggregation.

# V. Appendix

## A. Ownership Validation

In this appendix, we validate our product market screen using a subsample of firms in the Prowess dataset. This subsample contains all firms that are owned by a parent firm, which gives us multiple firms with common ownership. This is a validation exercise because we have strong reason to believe that these jointly-owned firms are indeed internalizing their effect on the one another. It also acts as a validation test for our various markup measures.

Prowess is a commercially available database collected by the the Centre for Monitoring the Indian Economy (CMIE). It contains financial data from the annual reports of public and private limited companies in India (those that are required to file annual reports). The sample size varies over the years 1989 to 2016, starting with only 500 firms in 1989, containing about 7500 firms by 2000 and up to 23,000 firms at its maximum. These are disproportionately medium and large firms. Prowess does not report employment, so our measure of labor is the total wage bill (including bonuses and pension contributions). Our measure for materials include raw material expenses and consumption of inventory and spare parts. Capital is measured by gross fixed assets, both structures and equipment. We deflate these variables using two-digit NIC wholesale price indexes.

We use Prowess, rather than the ASI, because it allows us to construct a subset of firms that are jointly owned by a parent firm (ASI does not include common ownership information). Specifically, Prowess has the financial ownership of companies which allows us to construct an indicator variable for firms that are wholly owned subsidiaries of other firms. This allows us to validate our markups and approach, using evidence of cooperation among firms that have the same ownership. This is a natural analysis to perform.[19] We

[19] Prowess also contains product level data, and another natural validation test is to see whether we show that firms internalize the impacts of their pricing on the profitability of their other products. Unfortunately, however, the inputs are not product specific. Although de Loecker et al. (2016) develop methods for creating proxies of the allocation of inputs, these are clearly only proxies and may contain considerable measurement error. Because the total inputs used are known, overestimation of inputs in one product leads to underestimation in the others, which causes an inverse relationship in estimated markups. This moves precisely against what the model predicts, but it would be driven by poor measurement of inputs rather than a lack of internal cooperation. This is precisely what we find when applying their methods.

define our sets of cooperating firms in equation (30) according to this joint ownership. In China, BKL found that this screen identified full cooperation among jointly-owned affiliates of private firms and also among Chinese state-owned enterprises at the province level.

We find similar validation results for India as presented in Table A. The table shows the results for the CD markups and CRS markups, respectively. The results for the CD markups show strong (indeed, complete) cooperation among firms at the 4-digit industry level. Consistent with theory, the narrowest definition of product markets generate the strongest results. If we define markets at the 2-digit level, for example, we find that firm markups only comove with their own market shares rather than the 2-digit market shares of the jointly owned firms. We interpret this as evidence that firms don't internalize their behavior on other jointly owned firms that operate in other product markets. At the 4-digit level, the coefficient on joint share is 0.096, which statistically significant at the 5 percent level despite focusing on only a small set of firms. The coefficient is comparable to those found for China. In contrast the coefficient on the firm's own share is smaller and statistically insignificant at the 4-digit level. Ignoring the statistically insignificant coefficient, this would give us an estimate of $\kappa = 1$. The results for the DLW markups are quite similar to those for the CD markups. For the case of the CRS markups, however, the results are less stark. We find a significant relationship between markups and both own share and the joint share. The values imply a lower value of $\kappa$, $\kappa = 0.45$, but the fit of the regression is also lower,. Recall that CRS is an imperfect measure in the presence of monopsony power because it attributes all profits to markups, rather than a combination of markups and markdowns. Thus, we are less troubled that the validation exercise is not as strong for the CRS measure. Nevertheless, we find a high level of cooperation with all three measures, and comparing the results for 2-digit and 4-digit industries, we see that firms internalize products that are more similar.

Table A—Regression Results Using All Affiliated Firms in Prowess, Trimmed Sample, 1989-2016

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | 4-digit | 2-digit | 3-digit | 4-digit | 2-digit | 3-digit | 4-digit |
| *Panel A: Dependent Variable = 1/Markup(DLW)* | | | | | | | |
| Firm's Share | -0.119*** | | | | -0.096** | -0.072* | -0.032 |
| | (0.041) | | | | (0.043) | (0.044) | (0.051) |
| Cluster's Share | | -0.061*** | -0.083*** | -0.115*** | -0.025 | -0.049** | -0.090** |
| | | (0.023) | (0.024) | (0.035) | (0.021) | (0.021) | (0.040) |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES |
| Observations | 26,927 | 26,927 | 26,927 | 26,927 | 26,927 | 26,927 | 26,927 |
| Adjusted $R^2$ | 0.695 | 0.695 | 0.695 | 0.695 | 0.695 | 0.695 | 0.695 |
| *Panel B: Dependent Variable = 1/Markup(CD)* | | | | | | | |
| Firm's Share | -0.132*** | | | | -0.099** | -0.097** | -0.040 |
| | (0.034) | | | | (0.041) | (0.043) | (0.052) |
| Cluster's Share | | -0.075*** | -0.083*** | -0.127*** | -0.036 | -0.037 | -0.096** |
| | | (0.020) | (0.022) | (0.030) | (0.024) | (0.027) | (0.048) |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES |
| Observations | 27,157 | 27,157 | 27,157 | 27,157 | 27,157 | 27,157 | 27,157 |
| Adjusted $R^2$ | 0.644 | 0.644 | 0.644 | 0.644 | 0.644 | 0.644 | 0.644 |
| *Panel C: Dependent Variable = 1/Markup(CRS)* | | | | | | | |
| Firm's Share | -0.283*** | | | | -0.233*** | -0.226*** | -0.153** |
| | (0.048) | | | | (0.053) | (0.054) | (0.064) |
| Cluster's Share | | -0.144*** | -0.168*** | -0.253*** | -0.053** | -0.060** | -0.135** |
| | | (0.024) | (0.027) | (0.042) | (0.025) | (0.029) | (0.055) |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES |
| Observations | 26,864 | 26,864 | 26,864 | 26,864 | 26,864 | 26,864 | 26,864 |
| Adjusted $R^2$ | 0.461 | 0.460 | 0.460 | 0.461 | 0.461 | 0.461 | 0.461 |

Notes: Robust standard errors clustered at firm level are in parentheses. Significance: ***: 1%, **: 5%, *: 10%. Cluster is defined as a group of firms jointly owned by a common owner. Various industry aggregation levels are employed, including 4-digit industry (in specifications 1, 4 and 7), 3-digit industry (in specifications 3 and 6), and 2-digit industry (in specifications 2 and 5). All regressions include a constant term.