Imperfect Competition in Product and Labor Markets.
A Quantitative Analysis*

Dario Tortarolo† Roman D. Zarate‡

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Abstract
We disentangle the extent of imperfect competition in product and labor markets using plant-level data. We derive a formula for the ratio between markups and markdowns assuming cost-minimizing firms that face upward-sloping labor supply and downward-sloping product demand curves. We then separate this combined measure of market power by estimating firm-level labor supply elasticities instrumenting wages with a different set of instruments including the use of intermediate inputs, input price shocks, and TFP shocks. Our results suggest that both markets exhibit imperfect competition, but the variation is mainly driven by markups. We also estimate the relative gains of removing market power dispersion on allocative efficiency, finding that markups are more important on TFP than markdowns.

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†University of Nottingham and Institute for Fiscal Studies. E-mail: dario.tortarolo@nottingham.ac.uk
‡World Bank, Washington, DC. E-mail: rzaratelasquez@worldbank.org

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The estimation of market power has been of long interest in economics. On the one hand, industrial organization and trade economists have developed different methods to measure *markups* because they provide relevant information on different market outcomes. For example, DeLoecker and Eeckhout (2017) show that the increase in average *markups* in the last three decades in the US can account for a number of secular trends that include the decrease in the labor share. On the other hand, recent studies in labor economics have made efforts to estimate labor market power because ignoring the existence of employer market power could lead to incorrect conclusions on the driving force behind changes in wage inequality (Manning, 2003b); and a monopsony model rationalizes different facts found by the employer-employee literature. For example, the fact that wages of workers with similar skills vary across firms (Card et al., 2018).

The question of whether labor markets and product markets are imperfectly competitive, however, has been approached separately for each market. While a large body of literature estimates *markups*, the empirical evidence on *markdowns* is still relatively new and has been growing substantially in the last decade. In this paper, we approach this question from an integrated perspective and propose a methodology to measure the extent of market power of firms in both product and labor markets using production-level data. We also show the usefulness of our framework with an application that measures the relative TFP gains of eliminating variable market power in product versus labor markets.

Although combined market power is the relevant metric for resource misallocation, disentangling product and labor market power matters for at least two reasons. First, it is important for policy concerned about efficiency to understand whether market power is on the product or the labor side. This can indeed be an important step toward determining which frictions governments should prioritize. Second, there are different implications for inequality depending on the source of market power. For example, labor market power exacerbates wage inequality because workers with similar characteristics receive different salaries depending on the firm they work for. Therefore, the estimates of *markdowns* are relevant for policy aimed at reducing wage inequality. In a similar vein, the estimates of *markups* are informative for consumption inequality. Recent literature has shown that basket consumption shares vary enormously across the income distribution and, as a result,

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1 We interpret “monopsony” or “oligopsony” as employers having wage-setting power.
2 The standard neo-classical model assumes that firms do not have market power in labor and, therefore, a worker’s wage only depends on its own ability and productivity. Some recent references that analyze labor market power are Kline et al. (2017), Garin and Silverio (2017), Azar et al. (2017), Caldwell and Danieli (2018), McKenzie (2019).
changes in markups may affect individuals differently.\textsuperscript{3}

The most standard technique in the literature to estimate markups using production data, is the method developed by DeLoecker and Warzynski (2012)—henceforth DW—based on the formula by Hall (1988). In this paper, we reinterpret this formula as a combined measure of market power for any variable input, including labor.\textsuperscript{4} We are able to separate this combined measure of market power into markups and markdowns by estimating the residual labor supply elasticity to the firm directly and by assuming an oligopsonistic market structure. We also show how our methodology can be used to decompose the misallocation due to product vs. labor market power.

In the first part of the paper, we present a simple model with cost-minimizing firms that have market power in both product and input markets. This model extends the method of DW by assuming that firms face an upward-sloping labor supply curve as in Card et al. (2018)—henceforth CCHK. From the first order condition with respect to any variable input, such as labor, we derive an equation that guides our empirical analysis. The equation establishes a theoretical relation between unobserved plant-level markups and markdowns, the observed participation of the variable input in total revenue, and the output elasticity of the variable input (DeLoecker et al., 2016; Dobbelaere and Kiyota, 2018).

The equation states that the ratio of product markups to labor markdowns is equal to the ratio of the output elasticity of labor and the share of labor cost in total output. We define the ratio of markups to markdowns as the combined measure of market power in both markets. Intuitively, the equation suggests that firms exert more market power when they get relatively more output out of the labor input than the cost it represents to the plant. This could be explained by firms setting prices above the marginal cost (markup) and/or firms setting wages below the marginal revenue product of labor (markdown).

In the second part of the paper, we propose different strategies to estimate the elements of our main equation which, ultimately, allow us to calculate market power. We start by estimating the output elasticity of labor using standard production function techniques. The ratio of this parameter and the share of labor cost in total output, which is observable in any production data, allows us to compute the combined measure of market power.

Our next step is to separate overall market power into markups and markdowns. To this end, we develop an empirical strategy to estimate markdowns using firm-level production data. We follow the Roy-type model developed by CCHK, in which workers have het-

\textsuperscript{3}For more about consumption inequality see Faber and Fally (2017), Jaravel (2016), Atkin et al. (2020).

\textsuperscript{4}Dobbelaere and Kiyota (2018) and Morlacco (2018) provide a similar interpretation.
erogeneous preferences for different workplaces and firms compete oligopsonistically. In particular, workers receive random productivity draws about their job place from an extreme value type distribution. From the model, we get a reduced-form equation for the relationship between labor and wages that we use to estimate the labor supply elasticity to the individual firm. Since this equation is endogenous by nature, we identify the coefficient of wages using a set of instruments that includes intermediate inputs and input price shocks.

Ideally, one would like to instrument wages per efficiency units with productivity shocks at the firm level. However, since TFP shocks are not observable, we adopt an old idea from the production function literature in which materials and the price of intermediate inputs in the local economy can work as a proxy for TFP shocks. Our exclusion restriction is that a positive correlation between changes in TFP and changes in the use of intermediate inputs or input price shocks within firms shifts the labor demand curve but not the labor supply curve to the firm. With the labor supply elasticities in hand, we are able to pin down markdowns through the standard formula that connects these two concepts. Finally, using the combined measure of market power and markdowns we back out markups through our main equation by estimating a product demand elasticity and assuming an oligopolistic market structure.

In the third part of the paper, we characterize firms and industry heterogeneity in terms of markups and markdowns. We study whether firms with higher markups also exert higher or lower monopsony power. Additionally, we explore the systematic relationship of markups and markdowns with plant characteristics, namely, total factor productivity (TFP), plant size, and exporter status.

Finally, we show how our framework can be used by providing an application that is relevant to the misallocation literature. Recent research has emphasized the role of market power dispersion on the functioning of input markets. In particular, Banerjee and Duflo (2005), Restuccia and Rogerson (2008), and Hsieh and Klenow (2009) suggest that the dispersion in firms’ marginal revenue works as a sufficient statistic for the functioning of input markets such as labor, capital, or intermediate inputs, and it may have important implications for resource misallocation. One of the factors that determines marginal revenue dispersion is market power (i.e., the fact that firms in the same industry exert different levels of

Although we believe that our strategy performs well in general, there are some potential threats to our exclusion restriction that cannot be ruled out, such as factors simultaneously affecting the use of materials and shifting the labor supply curve to the firm.
market power). Therefore, in our application, we proceed to measure the relative TFP gains of eliminating variable market power in product vs. labor markets. We extend the quantitative model from Hsieh and Klenow (2009)—henceforth HK—by assuming that consumers face constant-elasticity demand curves and that workers have idiosyncratic preferences for their work place based on an extreme value type distribution. We expand their formula and show that the effect of market power dispersion on TFP depends on two parameters: the labor supply elasticity and the product demand elasticity.

For the empirical analysis, we use the panel of Colombian manufacturing plants, EAM, spanning the period 2002-2014. Our results confirm that product and labor markets (in the manufacturing sector) are not perfectly competitive, but the variation of combined market power across industries seems to be driven by markups. That is, manufacturing firms exert more market power in product than in labor markets. On average, manufacturing plants set prices 78% higher than marginal costs, and pay wages 11% lower than the marginal revenue product of labor.

We find a negative correlation between product and labor market power and more elastic labor supply curves for unskilled workers. For the last two results, we provide additional evidence for the mechanisms that could be at play. Similar to the first result, we obtain a positive correlation between product market power and productivity, size, and exporter status, and a negative correlation of these measures with labor market power. We provide some potential explanations of these patterns based on a theory pioneered by Manning (2010) about firm sorting, labor market power, and spatial economics. Regarding resource misallocation, we show that the relative TFP gain of reducing the dispersion of markups is more important than reducing the dispersion of markdowns. In our exercise, TFP increases approximately 20% when we remove market power dispersion; 26% when we only remove markup dispersion, and 2.5% when we only remove markdown dispersion.

Related Literature

This paper combines classic ideas from the theory of monopoly and monopsony (Robinson, 1933) with recent methods from industrial organization and labor economics to estimate production functions and market power. Our paper is closely related to three different

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6For example, the higher labor supply elasticity for unskilled workers could be rationalized by the presence of a minimum wage. In the cost minimization problem one can include an additional restriction that accounts for the minimum wage that will be more binding for firms with a higher composition of unskilled workers.
strands of literature. First, to the literature that has followed Hall’s approach to estimate market power. Second, to a recent literature interested in estimating labor market power and, third, to the literature that has studied the role of market power on misallocation. Our main contribution is to disentangle product and labor market power measures with a novel methodology, and to measure the relative importance of each measure at the aggregate level. In particular, we study how the dispersion of product and labor market power affects allocative efficiency. This analysis is relevant for regulators and policy makers on both markets.

Our work is closely related to the literature that has extended the seminal work of Hall (1988) in different directions. On the product market side, we build on recent work by DW and DeLoecker et al. (2016) who estimate the relationship between prices and marginal costs using plant-level production data in an environment in which firms exert market power and are heterogeneous. In this sense, it is also related to recent research that addresses product and labor market imperfections simultaneously based on Hall’s approach. Crépon et al. (2005) and Dobbellaere and Mairesse (2013) estimate production functions using GMM methods and lagged values of factor inputs as instruments. In particular, Dobbellaere and Mairesse (2013) estimate a parameter of joint market imperfections from the difference between output elasticities of labor and materials and their revenue shares. The authors also classify industries into different regimes based on the degree of market power in product and labor markets. In addition, Dobbelaere and Kiyota (2018) explore the relationship between a firm’s internationalization status and the degree of market imperfection in product and labor markets, and Lu et al. (2019) analyze the effect of foreign direct investment on labor market power.

Other papers also use Hall’s approach to study market power using expenditure in inputs instead of labor. For example, Morlacco (2018) studies the aggregate implications of market power in intermediate inputs for French manufacturing firms. Similarly, Ganapati et al. (2016) use input expenditures to estimate markups and measure the incidence of input taxes on the relative welfare of manufacturing producers and consumers in the U.S.

On the labor market side, this article fits into a new literature that has attempted to measure labor market power (e.g., see Manning (2010) and Ashenfelter et al. (2010) for recent reviews; and Kline et al. (2017) and Garin and Silverio (2017) for new identification strategies). First, it is related to a new literature that considers imperfect labor markets to explain the relationship between the dispersion of firms’ productivity and wage inequality (Card
et al., 2018), as well as labor market concentration (Azar et al., 2017) and wage stagnation in the U.S. (Naidu et al., 2018). Moreover, it is also related to a new literature in labor economics that has focused on understanding the role of labor market power. For instance, it is related to Caldwell and Danieli (2018) and Caldwell and Harmon (2018) that measure the effect of outside options on labor market power, to McKenzie (2019) that studies the relationship between trade and labor market power, and to Berger et al. (2019) that studies the effect of labor market power on welfare in U.S. local economies.

Our study differentiates from previous work in two meaningful ways. First, we estimate production functions using the method of Ackerberg et al. (2015) which addresses endogeneity issues derived from unobserved productivity and input choices. Second, and unlike previous studies, we estimate a labor supply Roy model using materials and input price shocks as an instrumental variable, which lets us identify the elasticity of labor supply to the individual firm directly. By combining tools from IO and the Labor literature, we estimate two equations in an over-identified setting, which imposes more discipline to the empirical analysis relative to other papers. Lastly, we connect the literature of markups, markdowns, and resource misallocation by measuring the relative gains in TFP of eliminating variable market power in product vs labor markets (Hsieh and Klenow, 2009; Baqaee and Farhi, 2020).

The proposed framework allows us to pin down policy-relevant parameters and elasticities that enable a better understanding of market outcomes, such as the extent of imperfect competition and its role on TFP and resource misallocation across industries. As such, the results from this research exhibit great promise of informing policy debates. Policymakers could target regulations and other policies aimed at competition and antitrust, trade, consumer, and employment protection. For example, in industries with higher labor market power, policies like minimum wages could reduce the markdown gap by limiting the rents that could be extracted from the workforce. Finally, in terms of future research it is important to separate both measures of market power to understand the effect of markups and markdowns on real income inequality.

The remainder of the paper is organized as follows. Section 1 lays the conceptual framework that guides the empirical analysis. Section 2 presents our empirical strategy based on DW and CCHK. We divide this section into two parts: a methodology for the production function estimation and a strategy to estimate labor supply elasticities at the firm level. Both methods rely on the fact that the use of intermediate inputs and input prices are good
proxies for productivity shocks. Section 3 describes the data for our empirical application. Section 4 reports our main results and characterizes firms and sectors according to product and labor market power. In Section 5, we quantify the negative relationship between market power dispersion in both markets and aggregate TFP following HK. Section 6 concludes.

1 Conceptual Framework

To estimate the extent of market power in product and labor markets, we derive a combined measure that consists of markups and markdowns at the firm level. To this end, we assume cost-minimizing firms free of any adjustment cost with the following production technology:

\[ Q_{it} = Q_{it}^1(\ldots, X_{it}^{V-1}, L_{it}, K_{it}, \omega_{it}), \] (1)

where \( X_{it}^v \) corresponds to the quantity of a variable input, \( V \) is the number of variable inputs, \( L_{it} \) corresponds to labor, \( K_{it} \) to capital stock, and \( \omega_{it} \) is a TFP measure. Let’s assume that firm \( i \) has market power in product markets and in labor markets as well, and that labor is an additional variable input. In other words, firm \( i \) behaves as a monopoly in the market of the good that it produces, and as a monopsony in the labor market. Then, the Lagrangian associated to the cost minimization problem is:

\[ \mathcal{L}(X_{it}^1, \ldots, X_{it}^{V-1}, L_{it}, K_{it}, \omega_{it}) = \sum_{v=1}^{V-1} P_{it}^v X_{it}^v + w_{it}(L_{it})L_{it} + r_{it}K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot)), \]

where \( P_{it}^v \) corresponds to the input price, \( r_{it} \) to the capital cost, and \( w_{it} \) to the wage that the firm pays which can differ across firms. The first order condition of this minimization problem with respect to any variable input is:

\[ w_{it} \left( 1 + \frac{1}{\epsilon_{it}^{Lw}} \right) = \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial L_{it}}, \] (2)

where \( \epsilon_{it}^{Lw} \) denotes the elasticity of labor supply to the firm, and therefore, the term between parentheses is the inverse of the markdown, \( MD_{it} \). The interpretation of this term is as follows: if wages at firm \( i \) increase by 1%, the share of workers that are willing to work at this firm increases by \( \epsilon_{it}^{Lw} \). By an envelope theorem argument, \( \lambda_{it} \) is the marginal cost of producing one unit of output. Rearranging terms and using the fact that we can express
the marginal cost as the ratio between prices and markups \( \lambda_{it} = \frac{p_{it}}{\text{MU}_{it}} \), then we arrive to a combined measure of market power, \( MP_{it} \):

\[
MP_{it} \equiv \frac{\text{MU}_{it}}{\text{MD}_{it}} = \frac{\theta_{it}^{L}}{\alpha_{it}^{L}},
\]

where the parameter \( \theta_{it}^{L} \) corresponds to the output elasticity with respect to labor, and \( \alpha_{it}^{L} \) to the wage bill share on total revenue or value added. This is the key equation that guides our empirical analysis. Note also that equation (3) can be generalized for any variable input \( X_{it}^{v} \) as:

\[
MP_{it}^{v} = \frac{\text{MU}_{it}}{\text{MD}_{it}^{v}} = \frac{\theta_{it}^{v}}{\alpha_{it}^{v}},
\]

where \( \alpha_{it}^{v} \) is the share of a variable factor \( v \) in total revenue (e.g., blue-collar workers) and \( \theta_{it}^{v} \) is the output-elasticity of factor \( v \). Markdown is defined as the gap between wage and marginal revenue product of labor, and markup is the gap between price and marginal cost. From the first order condition of the firm’s profit maximization problem we can also express markups and markdowns as:

\[
\text{MU}_{it} \equiv \frac{p_{it}}{m_{c_{it}}} = \frac{|\rho_{it}^{p}|}{|\rho_{it}^{p}| - 1}, \quad \text{MD}_{it} \equiv \frac{w_{it}}{\text{MRPL}_{it}} = \frac{e_{it}^{\text{Lw}}}{e_{it}^{\text{Lw}} + 1},
\]

where \( \rho_{it}^{p} \) is the product-demand elasticity and \( e_{it}^{\text{Lw}} \) is the elasticity of labor supply to the firm.\(^7\) The first equation is a rearrangement of the Lerner index, while the second equation is the counterpart for monopsonies.

The degree of market power can be deduced as soon as \( \alpha_{it}^{v} \) and \( \theta_{it}^{v} \) are pinned down. Note that \( \alpha_{it}^{v} \) is typically observed in any production data and \( \theta_{it}^{v} \) is a parameter that requires estimation. In addition, there is an identification problem since market power is coming from two different sources. One way of separating them is to estimate either \( \rho_{it}^{p} \) and/or \( e_{it}^{\text{Lw}} \). Our strategy consists of estimating market power using standard production function techniques as in DeLoecker and Warzynski (2012), then to estimate the labor supply elasticity to the individual firm to compute markdowns, and finally back out markups.

Several recent papers have estimated firm-level markups by focusing on the right hand side of equation (4), implicitly assuming perfect competition in labor markets (e.g., see De-

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\(^7\)Based on this equation, the more inelastic the labor supply curve to the employer, the wider the gap between the marginal product of labor and the wage. This gap is also known as the “rate of exploitation” (Hicks, 1932).
In that special case, workers are paid their marginal product of labor and *markdowns* are equal to one. When labor markets are not competitive, however, the right hand side of equation (4) identifies market power in both product and labor markets.

In this paper we argue that for policy concerned about efficiency and inequality, it is important to separate both measures. For instance, we can imagine a situation in which a producer is selling a commodity in a context where international prices are given and who is operating in a labor market with frictions. In this case, the *markup* is close to one (the price is close to the marginal cost) and the *markdown* will be lower than one (workers are paid a wage below their marginal revenue product). Hence, the source of imperfect competition comes from the labor market and not from the market of goods. With our proposed framework we can separate combined market power into *markups* and *markdowns* at the firm and industry level.

## 2 Empirical Strategy

### 2.1 Production function estimation

The estimation and identification of $\theta_{li}^v$ has received a lot of attention in the IO literature. One way of getting consistent output elasticities is to estimate production functions using “proxy methods” developed by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015). This method is also used by DeLoecker and Warzynski (2012) who estimate *markups* at the firm level. We adopt the same approach as Ackerberg et al. (2015) (ACF, hereafter) to estimate the output elasticity with respect to labor which is the key parameter that allows to pin down our combined measure of market power.

Since the approach we adopt is a standard technique to estimate production functions, we refer the reader to Appendix A for more details on the 2-step method to estimate the output elasticity of variable inputs. In practice, the implementation of this method requires

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8 In appendix D of DeLoecker et al. (2016), the authors consider imperfect competition in input markets as well. They argue that their estimates of the effect of the trade reform liberalization in India on *markups* is unlikely since they include firm-product fixed effects and show evidence that there are not differential effects of the trade reform across initial firm sizes or if a firm belongs to a large business group. In other words, they argue that it is unlikely that input supply elasticities change with the trade liberalization episode so that their point estimates do not change in a world with *markdowns*.

9 OLS estimates are typically biased since observed inputs are chosen as a function of unobserved determinants of production. The idea of the “proxy methods” is to assume that an input (e.g., material) is a strictly increasing function of a scalar, firm-level, unobserved productivity shock (conditional on capital stock). One can then invert this input demand function, and thus control for the unobserved productivity shock by conditioning on a nonparametric representation of that inverse function (i.e., a nonparametric function of capital stock and materials).
parametric assumptions on the functional form of the production function (equation 12). We follow DeLoecker and Warzynski (2012) and consider a Cobb-Douglas and a Translog specification:

\[ y_{it} = \beta l_{it} + \beta k_{it} + \omega_{it} + \eta_{it} \] (6)
\[ y_{it} = \beta l_{it} + \beta k_{it}^2 + \beta l_{it}^2 + \beta l_{it} k_{it} + \omega_{it} + \eta_{it} \] (7)

where \( y \) is log-output (value added), \( l \) is log-labor, and \( k \) is log-capital. For a Cobb-Douglas technology, the output elasticity of labor is given by \( \theta_{it}^L = \beta_l \) and is constant across plants and time. In the Translog case, this elasticity is \( \theta_{it}^L = \beta_l + 2\beta_{ll} l_{it} + \beta_{lk} k_{it} \) and varies across plants and time. To get more variation in our measure of market power we estimate these functions by 2-digit industries.

To decompose aggregate market power into markups and markdowns we adopt a discrete choice method of the IO literature based on Berry (1994) and Berry et al. (1995) -henceforth BLP- that allows to pin down price-demand elasticities or labor-supply elasticities. However, since it is easier to define a labor market than a product market, our identification hinges on the estimation of residual labor supply elasticities. We define a labor market as region-sector-year cell. We based our theoretical framework on the model developed by CCHK, which is similar to Roy models that assume idiosyncratic logistic shocks. In the next section we explain our empirical strategy to estimate labor supply elasticities in more detail.\(^{10}\)

2.2 Labor supply elasticity

We pin down markdowns by estimating labor supply elasticities to the individual firm.\(^{11}\) Then, we can identify the markup using our main equation (4). To this end, we will use demand estimation techniques from the IO literature, yet the application is on labor markets instead of product markets. Let’s assume that for any worker \( n \), the indirect utility of

\(^{10}\)It is important to note that our model is over-identified, in the sense that it is possible to follow alternative strategies to estimate the same objects of interest. For instance, for single product firms, we could regress quantities on prices instrumenting the price with TFP shocks to identify the product-demand elasticity and pin down the markup. Then using our main equation we can back out the markdown. However, since we are using firm-level production data, it is much easier to define a labor market than a product market. The reason is that we would need customs data to determine competition in product markets, in which foreign firms compete with domestic firms. Hence, in principle, we only estimate labor supply elasticities. In addition, we can use other instruments as well, namely, the classic BLP instruments such as leave-out mean prices, inputs, or wages in each industry.

\(^{11}\)Note that this elasticity is different from the macro labor supply elasticity based on labor market models in which workers decide between leisure, consumption, and hours of work.
working at firm $i$ is given by:

$$U_{nit} = x_{it} \gamma + \beta w_{it} + \psi_i + e_{it} + \epsilon_{nit} \quad (8)$$

where $w_{it}$ is the wage that firm $i$ offers, $\psi_i$ is a firm fixed effect, $x_{it}$ are firm-specific characteristics that affect the decision of the worker, and $\epsilon_{nit}$ captures idiosyncratic preferences for working at firm $i$ that we assume are independent draws from a type I Extreme Value distribution. By the properties of the exponential distribution family, the probability of working at firm $i$ in period $t$ (or equivalently the labor share of firm $i$) is given by:

$$s_{it} = \frac{\exp(x_{it} \gamma + \beta w_{it} + \psi_i + e_{it})}{\sum_k \exp(x_{kt} \gamma + \beta w_{kt} + \psi_k + e_{kt})} \quad (9)$$

We can construct labor shares for each firm at the industry-level from our data. Moreover, taking logs at both side of equation (9), we estimate the following equation:

$$\ln s_{it} = x_{it} \gamma + \beta w_{it} + \psi_i + \gamma_{m(i,t)} + e_{it} \quad (10)$$

where $\gamma_{m(i,t)}$ is a market fixed effect defined as a region-industry-year cell. Note that we get rid off the denominator in (9) by including market fixed effects. A simple OLS regression of equation (10) leads to a biased $\beta$ because the wage that firm $i$ posts is correlated with the error term. For example, firm specific shocks such as better amenities affect both the error term and the wage that firm $i$ posts. Therefore, to identify the coefficient of interest, $\beta$, we rely on IV regressions and instrument $w_{it}$ with the log of intermediate inputs or materials $m_{it}$. Figure 1 provides a simple representation for the mechanism of our identification strategy.

We consider that materials is a good instrument for wages for two reasons. First, in the production function estimation literature materials is widely used as a proxy for productivity (Levinsohn and Petrin, 2003) and, second, our exclusion restriction implies that after controlling for firm fixed effects, a higher usage of materials does not shift the labor supply curve, an assumption we believe to be plausible in practice.\(^{12}\) Finally, the elasticity of the labor supply to the individual firm implied by the model is:

$$\frac{\partial s_{it}}{\partial w_{it}} = \beta w_{it} (1 - s_{it}) \quad (11)$$

\(^{12}\)The greatest threat to our exclusion restriction is that some labor supply shocks could also affect the use of intermediate inputs at the firm level.
Identification of labor supply

TFP shocks $\rightarrow$ ↑ intermediate inputs $\rightarrow$ ↑ labor demand

Figure 1: Identification of the labor supply to the firm

Note: This figure illustrates the spirit of our identification strategy to estimate the slope of the labor supply to the individual firm. Namely, the firm receives a productivity shock that leads to an increase in the consumption of intermediate inputs, which in turn increases the demand for workers. This shift in the labor demand identifies the slope of the labor supply.

A more sophisticated and flexible strategy would be to estimate Random Coefficient logit models of labor supply to get variation of the labor supply elasticity at the firm level using the empirical methodology from BLP. However, we believe that our preliminary results are consistent with the Bargaining literature in labor markets. Finally, note that equation (10) can be estimated separately for different types of workers (e.g., by skill groups). In the empirical section, we explore the heterogeneity by high-skilled and low-skilled workers.

3 Production Data

The empirical analysis relies on plant-level production data from Colombia’s Annual Manufacturing Survey (EAM) collected by DANE, the Colombian statistical agency. The EAM is a uniquely rich census of manufacturing plants with 10 or more employees. It provides standard plant survey information plus much more rare data on physical quantities and unit values of manufactured products and used inputs.\footnote{The more standard variables are: sales, value added, input use, investment, employment and wage bill of professional production workers, non-professional production workers, and administrative workers; and broader information such as ownership structure, foreign capital participation, year in which activities began, geographic location, and industry affiliation at the four-digit level of the ISIC Revision 3.} We observe approximately 5,000-
7,000 plants in each year, producing in and purchasing from approximately 4,000 distinct eight-digit product codes (comparable to the 6-digit codes of the Harmonized System).

In the analysis we narrow the attention to the period 2002-2012. The definition of the variables used in the analysis follows closely a series of papers that have used the EAM census in the past (e.g., Eslava et al. (2013)). Employment includes both paid and unpaid production and administrative workers. Labor costs include wages, salaries, bonuses and any supplemental labor costs. To consider differences in quality or productivity, labor is computed in efficiency units, where physical units are normalized by the ratio between the plant average wage and the average industry wage. We use perpetual inventory methods to construct plants’ stock of capital. Intermediate inputs include materials, electricity, fuels, and other expenditures. All variables are deflated using industry-level deflators.14

In constructing the final working data file, we also follow the cleaning procedures adopted by Kugler and Verhoogen (2012) for the same data. Namely, we drop plants reported to be cooperatives, publicly owned, or owned by a religious organization; we also drop plants that have missing values on the key variables;15 we drop any plant-year observation for which a key variable differed by more than a factor of 6 with respect to the median of the plant in the whole period of analysis; we winsorize the key variables within each year to the values of percentile 1 and 99.16

Table 1 reports basic summary statistics. The final sample includes 80,329 plant-year observations. Plants employ an average of 75 workers and there is large variation across plants-years. The share of skilled workers is on average 37 percent and the share of unskilled workers is 63 percent. On average, the wage per worker is twice as large for skilled than unskilled workers.17 The table also shows that materials is a pretty important component of the production structure followed by capital and electricity. Note also that about 33 percent of the plants are single-product and 67 percent are multi-product manufacturing an average of 4 products. Over the period of analysis, 24 percent of the plants exported at least once, and 18 percent of the plants imported inputs for their production process.

Table 2 shows some variation of our main variables by 2-digit ISIC industries. The largest

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14 The use of industry-level deflators raises the issue of the possibility that prices may vary across plants. We correct for this issue by following Eslava et al. (2013) who use plant-level output (input) prices from the survey to construct physical quantities of output (inputs).

15 The key variables are: gross output, number of workers, wage bill, wage per worker, capital, and intermediate inputs.

16 The results are robust to a variety of different bounds for the winsorizing procedure and a different strategies to deal with outliers as well.

17 Skilled workers are administrative and professional production workers, and unskilled workers are production workers without a professional degree.
Table 1: Summary Statistics

| Variable                   | Mean   | Std. Dev. | 10th Perc. | 50th Perc. | 90th Perc |
|----------------------------|--------|-----------|------------|------------|-----------|
| Labor force                | 74.74  | 135.58    | 8          | 27         | 178       |
| Skilled                    | 26.39  | 51.29     | 2          | 8          | 66        |
| Unskilled                  | 46.59  | 87.73     | 4          | 16         | 43        |
| Share Skilled              | 37.09% | 0.22      | 11.76%     | 33.33%     | 68.00%    |
| Wage per worker            | 16.73  | 9.89      | 8.53       | 14.01      | 27.45     |
| Wage per skilled worker    | 23.24  | 19.36     | 7.48       | 18.39      | 44.52     |
| Wage per unskilled worker  | 13.44  | 11.06     | 8.14       | 11.77      | 19.35     |
| Materials (Share in total Revenue) | 55.07% | 0.19    | 29.78%     | 54.96%     | 81.33%    |
| Electricity (Share in total Revenue) | 2.18%  | 0.032  | 0.60%      | 1.22%      | 4.91%     |
| Capital (Share in total Revenue) | 42.41% | 3.53   | 4.60%      | 21.61%     | 78.53%    |
| Revenue (millions pesos)   | 13106.33 | 37436.79 | 299.91    | 1728.34    | 28888.42  |
| VA per worker (millions pesos) | 52.14  | 136.64    | 9.56       | 27.99      | 97.27     |
| Single product             | 32.87% | 0.47      | 0          | 0          | 1         |
| Number of products         | 3.56   | 3.53      | 1.00       | 2.00       | 8.00      |
| Importer                   | 0.18   | 0.39      | 0.00       | 0.00       | 1.00      |
| Exporter                   | 0.24   | 0.43      | 0.00       | 0.00       | 1.00      |

Note: This table provides summary statistics of our main variables using the final sample of EAM (80,329 plant-year observations). The data span the period 2002 to 2012. Nominal variables are expressed in million of Colombian pesos from 2008.

2-digit industry is Food and Beverages, followed by Clothing, Chemicals, and Plastic products. They account about 50 percent of employment in manufacturing and observations in the sample (Columns 3 and 4 of Table 2). The average share of labor costs on value added is 0.471 (this is $\alpha_L$ in equation 3). These values suggest that a plausible empirical measure of market power will require output-labor elasticities from the production function estimation to be larger than 0.471. In other words, under perfect competition in product and labor markets $\theta^n_L$ should be equal to 0.471. Note also that the variation presented in columns (4) and (5) could partly reflect differences in technology and labor market frictions across industries, which suggests that we need to allow for differences in production function parameters as part of the procedure to estimate our measure of market power. Therefore, in our analysis we report results estimating heterogeneous coefficients by industry.

4 Results

In this section we describe the empirical results. First, we estimate production functions to construct our combined measure of market power. Second, we estimate the elasticity of labor supply to the individual firm and compute plant-level markdowns. Finally, we use the two strategies to back out markups and correlate all these measures with plant characteristics.
| ISIC N (%) | Labor share | Wagebill /VA |
|------------|-------------|--------------|
| (1)        | (2)         | (3)          | (4)          | (5)          |
| Food products and Beverages | 15 | 15743 | 19.60% | 22.55% | 0.422 |
| Tobacco products | 16 | 56 | 0.07% | 0.21% | 0.319 |
| Textiles | 17 | 3701 | 4.61% | 7.00% | 0.517 |
| Wearing apparel, dressing and dyeing of fur | 18 | 8285 | 10.31% | 10.84% | 0.527 |
| Leather and leather products | 19 | 3459 | 4.31% | 3.21% | 0.496 |
| Wood, cork, and straw products | 20 | 1537 | 1.91% | 0.92% | 0.509 |
| Paper and paper products | 21 | 2119 | 2.64% | 3.28% | 0.445 |
| Publishing, printing and media | 22 | 5310 | 6.61% | 4.81% | 0.482 |
| Chemicals | 24 | 6849 | 8.53% | 10.31% | 0.394 |
| Rubber and plastic | 25 | 6565 | 8.17% | 7.88% | 0.479 |
| Non-metallic mineral products | 26 | 4007 | 4.99% | 5.68% | 0.453 |
| Basic metals | 27 | 1567 | 1.95% | 2.40% | 0.477 |
| Fabricated metal products | 28 | 5442 | 6.77% | 4.81% | 0.499 |
| Machinery and equipment | 29 | 4799 | 5.97% | 4.45% | 0.515 |
| Office, accounting and computing machinery | 30 | 34 | 0.04% | 0.02% | 0.413 |
| Electrical machinery and apparatus | 31 | 1663 | 2.07% | 2.23% | 0.475 |
| Radio, TV and communication equipment | 32 | 185 | 0.23% | 0.20% | 0.542 |
| Medical, precision and optical instruments | 33 | 664 | 0.83% | 0.56% | 0.496 |
| Motor vehicles, trailers and semi-trailers | 34 | 1865 | 2.32% | 2.37% | 0.499 |
| Other transport equipment | 35 | 501 | 0.62% | 0.87% | 0.502 |
| Furniture | 36 | 5526 | 6.88% | 4.93% | 0.509 |
| Total | 80329 | 100% | 0.471 |

Note: This table shows summary statistics by 2-digit industry.

4.1 Output elasticities and market power

In this section we report the estimates of combined market power in product and labor markets. As highlighted in equation (4), the key ingredient to compute this measure is the output elasticity of labor. Table 3 displays estimates of the output elasticities of labor and capital. Column (1) shows OLS estimates as a benchmark, column (2) absorbs some unobserved heterogeneity through plant fixed effects, and column (3) presents the estimates using the ACF method. The ACF is our most preferred specification and the one we use to compute market power. In the Cobb-Douglas case (Panel A) the output elasticities are the input coefficients in the production function, and thus constant across plants. In column (3), the labor coefficient is 0.9, while the capital coefficient is 0.2. In the Translog case (Panel B) the output elasticity varies across plants and we report the average and standard deviation. The average output elasticities are very close to the Cobb-Douglas case.\textsuperscript{18} The last row of each panel reports the average returns to scale which are slightly higher than 1.\textsuperscript{19}

\textsuperscript{18}Note that the number of observations is lower in the ACF method. This is because the 2-step GMM uses the lag of labor as an instrument and therefore we lose the observations from the base year.

\textsuperscript{19}A similar result is reported in the paper by DeLoecker et al. (2016) where 68 percent of the sample exhibits increasing returns to scale.
Table 3: Production Function Estimation

|                  | OLS  | FE   | ACF  |
|------------------|------|------|------|
|                  | (1)  | (2)  | (3)  |
| **Panel A: Cobb-Douglas** |      |      |      |
| Labor            | 0.859 | 0.622 | 0.900 |
|                  | (0.012) | (0.033) | (0.105) |
| Capital          | 0.203 | 0.073 | 0.200 |
|                  | (0.009) | (0.023) | (0.120) |
| Observations     | 71,928 | 71,928 | 56,146 |
| RTS              | 1.062 | 0.695 | 1.100 |
| **Panel B: Translog** |      |      |      |
| Labor            | 0.848 | 0.629 | 0.904 |
|                  | (0.117) | (0.068) | (0.138) |
| Capital          | 0.209 | 0.075 | 0.212 |
|                  | (0.105) | (0.032) | (0.089) |
| Observations     | 71,928 | 71,928 | 56,146 |
| Average RTS      | 1.057 | 0.704 | 1.117 |

Note: This table reports the output elasticities for the production function. Elasticities are computed by industries and then averaged. Column 1 reports the results for OLS with industry and year fixed effect. Column 2 reports the results for the estimation that include firm and year fixed effects. And column 3 the results for ACF method. Panel A considers a Cobb-Douglas production function, and panel B a Translog production function. RTS reports average returns to scale, which is the sum of the output elasticities.

With these estimates in hand and data on labor costs and value added, we compute the product-labor market power for each plant. Table 4 displays summary statistics of the distribution of market power across firms. In the Cobb-Douglas specification, the average is 2.24 and the median is 2.02. There is also considerable variation across firms. The results are very similar for the Translog specification. The correlation between market power computed based on the Cobb-Douglas and Translog coefficients is high at 0.938. We will report all our results using the Cobb-Douglas market power. In Table 5 we show average market power by 2-digit industries. Our estimates suggest that Paper, Publishing, Food and beverages, Basic metals, Electrical machinery are the least competitive industries. Figure 2 shows that dispersion across firms is high and that the distribution is highly skewed, with a large mass of firms on the left-end of the distribution and a long tail on the right of the distribution.

In terms of the literature, our estimates are comparable to recent research that measured market power using the method proposed by DeLoecker and Warzynski (2012). These papers assume perfect competition in labor markets and thus interpret this measure as a price-cost markup. For instance, DeLoecker and Warzynski (2012) obtain median markups in the range of 1.17-1.28 for Slovenian manufacturing firms, with substantial variation across
Table 4: Market Power - Summary Statistics

|                                | Mean | St. Dev. | p25  | p50  | p75  |
|--------------------------------|------|----------|------|------|------|
| Market Power (Cobb-Douglas)    | 2.24 | 0.78     | 1.73 | 2.02 | 2.50 |
| Market Power (Translog)        | 2.20 | 0.70     | 1.74 | 2.03 | 2.46 |
| Correlation                    |      |          |      |      | 0.938|

Note: This table reports summary statistics for our measures of market power. These are computed using equation (4) in the main text. Outliers above and below the 2nd and 98th percentiles are trimmed.

Table 5: Median market power by industry

| Industry                          | CD   | TL   |
|-----------------------------------|------|------|
| All industries                    | 2.02 | 2.03 |
| Food products and Beverages       | 2.09 | 2.14 |
| Textiles                          | 1.82 | 1.86 |
| Apparel                           | 1.96 | 1.96 |
| Leather and leather products      | 2.04 | 2.05 |
| Wood, cork, and straw products    | 1.94 | 1.88 |
| Paper and paper products          | 2.27 | 2.20 |
| Publishing, printing and media    | 2.21 | 2.11 |
| Rubber and plastic                | 1.93 | 1.93 |
| Basic metals                      | 2.07 | 2.15 |
| Fabricated metal products         | 1.98 | 2.00 |
| Machinery and equipment           | 2.03 | 2.02 |
| Electrical machinery and apparatus| 2.04 | 2.20 |
| Medical instruments               | 1.91 | 1.95 |
| Motor vehicles and trailers       | 2.03 | 1.96 |
| Other transport equipment         | 2.03 | 2.00 |
| Furniture                         | 2.03 | 2.03 |

Note: The table reports the median market power by industry. CD stands for Cobb-Douglas and TL stands for Translog. Many industries that appear in Table 2 are left out the analysis because they have few observations and thus the GMM procedure is not well-behaved.

DeLoecker et al. (2016) estimate higher markups for Indian manufacturing firms. They find mean and median markups of 2.70 and 1.34 for a Translog specification, with considerable variation across sectors and across firms within sectors. DeLoecker and Eeckhout (2017) use balance sheet data for U.S. firms and find an average markup of 1.18 in 1980 and 1.67 in 2014. The variation is also quite large and goes from 1.15 (WalMart) to 2.71 (Google). Garcia-Marin and Voigtlander (2015) find mean and median markups of 1.486 and 1.248 for Chilean manufacturing firms that vary between 0.5 and 5.6. And using the same Chilean data Lamorgese et al. (2014) find average markups by sector between 1.32 and 1.88.

Given our relatively high estimates of market power, the next natural question is whether this result is driven by imperfect competition in product or labor markets. In the follow-
Market Power
MP (Cobb-Douglas) MP (Translog)

Figure 2: Distribution of market power

Note: This figure shows the distribution of market power across firms for both production functions: Cobb-Douglas and Translog.

In this section, we disentangle these two sources by estimating labor supply elasticities to pin-down markdowns and, finally, back out markups.

4.2 Labor supply elasticities

In this section, we turn to the estimation of equations (10) and (11) that are used to derive plant-level markdowns (tables 6 to 8). The exercise is done for three different instruments: materials (panel A), electricity (panel B), and number of used inputs (panel C). We interpret the variation introduced by these variables as proxies for productivity shocks that shift the labor demand and therefore allow us to identify labor supply elasticities to the individual firm. Intuitively, when a firm receives a positive shock, the use of intermediate inputs increases, the labor demand shifts up, and the number of workers hired by the firm increases (Figure 1). Our exclusion restriction implies that after controlling for firm fixed effects workers do not supply labor to firms based on the use of intermediate inputs. In addition, labor supply shocks are not correlated with the use of intermediate inputs.

Table 6 shows the results when we use total number of workers hired by each firm as our dependent variable. The first stage of the IV estimation suggests that there is a strong, positive, and similar-in-magnitude correlation between wage per worker and materials.
(panel A) and electricity (panel B), but it is weaker in the case of the number of inputs (panel C). In the second stage, we use the variation from these instruments to identify the coefficient of interest $\beta$ from Equation (10). The results are presented in columns (5) and (6). When we only include market fixed effects, the three IV estimates give a positive and statistically significant effect. Reassuringly, the three specifications provide very similar coefficients. If we also add firm fixed effects to control for unobserved heterogeneity, then the coefficients become larger but are still similar in magnitude.

Table 6: Labor Supply

| Dep variable | First Stage | OLS | IV |
|--------------|------------|-----|----|
|              | (1)        | (2) | (3) | (4) | (5) | (6) |
|              | Wage       | Labor Market Share | Labor Market Share |
| Panel A: Instrument Materials (log) |          |      |     |     |     |
| Materials (log) | 2.1563*** | 0.3374*** | 0.0645 | 0.038 |
| Wage | 0.0555*** | -0.0128*** | 0.2007*** | 0.5563*** |
| F statistic-FS | 20592 | 1820.44 | 77989 | 77989 |
| N | 77989 | 77989 | 77989 | 77989 |
| Panel B: Instrument Electricity (log) |          |      |     |     |     |
| Electricity (log) | 2.4255*** | 0.3813*** | 0.0599 | 0.0512 |
| Wage | - | - | 0.2248*** | 0.5746*** |
| F statistic-FS | 1626.64 | 57.76 | 79503 | 79503 |
| N | 79503 | 79503 | 79503 | 79503 |
| Panel C: Number of Inputs (log) |          |      |     |     |     |
| Number of inputs | 1.7970*** | 0.0978 | 0.1197 | 0.0952 |
| Wage | - | - | 0.2569*** | 12.312 |
| F statistic-FS | 225.368 | 1.05504 | 78000 | 78000 |
| N | 78000 | 78000 | 78000 | 78000 |
| Market fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | No | Yes | No | Yes | No | Yes |

Note: Labor supply elasticity results for the pool of workers. The first two columns show the results for the First Stage in which different sets of instruments are used for wage per worker, the third and fourth column the OLS point estimates, and the fifth and sixth columns the IV point estimates. Even columns estimate the labor supply elasticity within firms. Standard errors are clustered at the firm level. A Market is defined as an industry, region, year unit. *$p<0.1$, **$p<0.05$, ***$p<0.01$.

In Tables 7 and 8 we explore the heterogeneity of labor supply by separating the analysis into skilled and unskilled workers. In both cases, columns (1) and (2) confirm that there is a strong and positive first stage. The coefficients and F-statistics suggest a stronger first stage.

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20 This could be due to the fact that the number of inputs captures an extensive margin response in the use of intermediate inputs and when we include firm fixed effects the variation might not be enough to identify the coefficient of interest. This problem is not present in the case of expenditure in materials since this measure captures an intensive margin response.

21 The estimation that uses the number of inputs as an instrument is meaningless because there is no first stage.

22 We define unskilled workers as production workers without a professional degree, and skilled workers as the sum of production workers with a professional degree and administrative workers.
stage for skilled workers. In the second stage, we find much larger labor supply coefficients for unskilled workers. In both tables, the results vary little when we use materials or electricity as an instrumental variable.

### Table 7: Labor Supply: Skilled Workers

| Dep variable | First Stage | OLS | IV |
|--------------|------------|-----|----|
|              | (1)        | (2) | (3) | (4) | (5) | (6) |
| Materials (log) | 4.1706*** | 0.7999*** | 0.1093 | 0.0998 | 0.0248*** | 0.0094*** | 0.1025*** | 0.1827*** |
| Wage | 0.0016 | 0.0009 | 0.0023 | 0.0236 |
| F statistic-FS | 1459.76 | 61.07 | 76785 | 76785 | 76785 | 76785 |
| N | 77685 | 77685 | 77685 | 77685 | 77685 | 77685 |
| Electricity (log) | 4.8250*** | 0.7022*** | 0.0979 | 0.1657 | 0.0979 | 0.1657 |
| Wage | - | - | 0.1054*** | 0.2492*** |
| F statistic-FS | 2429.01 | 17.96 | 78239 | 78239 | 78239 | 78239 |
| N | 77685 | 77685 | 77685 | 77685 | 77685 | 77685 |
| Number of inputs | 3.1152*** | 0.0726 | 0.2113 | 0.2373 | 0.2113 | 0.2373 |
| Wage | - | - | 0.1719*** | 18.578 |
| F statistic-FS | 217.36 | 0.093 | 76796 | 76796 | 76796 | 76796 |
| N | 76796 | 76796 | 76796 | 76796 | 76796 | 76796 |

Note: Labor supply elasticity results for skilled workers. The first two columns show the results for the First Stage in which different sets of instruments are used for wage per worker, the third and fourth column the OLS point estimates, and the fifth and sixth columns the IV point estimates. Even columns estimate the labor supply elasticity within firms. Standard errors are clustered at the firm level. A Market is defined as an industry, region, year unit. *p<0.1, **p<0.05, ***p<0.01.

Overall, the IV regressions from Tables 6, 7, and 8 show that our instruments perform very well. We also believe that our identification assumption seems plausible since it is not clear why workers would supply labor to a firm that uses more materials in response to a productivity shock. Hence, since the three instruments provide very similar results, in the rest of the paper we focus the attention to the labor supply estimates that use materials as an instrumental variable.\(^{23}\)

Finally, we translate these estimates into labor supply elasticities to the individual firm using equation (11). Table 9 reports some summary statistics and Figure 3 presents the distribution of labor supply elasticities across plants. For the pool of workers, we find median elasticities of 2.74 and 7.62 for specifications with market FE and firm FE, respectively, with relatively little variation across sectors. However, there is more variation when we split

\(^{23}\)We choose the estimates that use materials because they are more precise (lower standard errors) compared to electricity and number of used inputs.
Table 8: Labor Supply: Unskilled Workers

| Dep variable         | First Stage | OLS       | IV        |
|----------------------|-------------|-----------|-----------|
|                      | (1) (2)     | (3) (4)   | (5) (6)   |
| Materials (log)      |             |           |           |
| Materials (log)      | 1.3617***   | 0.2820*** |           |
|                      | 0.0516      | 0.0458    |           |
| Wage                 |             |           |           |
| Wage                 | 0.0196**    | 0.0056**  | 0.3462*** | 0.8016*** |
|                      | 0.0096      | 0.0028    | 0.0131    | 0.1304    |
| F statistic-FS       | 696.40      | 37.911    |           |
| N                    | 75963       | 75963     | 75963     | 75963     |
| Electricity (log)    |             |           |           |
| Electricity (log)    | 1.4687***   | 0.2918*** |           |
|                      | 0.0572      | 0.0881    |           |
| Wage                 |             |           |           |
| Wage                 | - -         |           | 0.3794*** | 0.8388*** |
|                      | - -         |           | 0.0153    | 0.2552    |
| F statistic-FS       | 659.28      | 10.97     |           |
| N                    | 77158       | 77158     |           |
| Number of inputs     |             |           |           |
| Number of inputs     | 0.8709***   | 0.3142**  |           |
|                      | 0.0905      | 0.1355    |           |
| Wage                 |             |           |           |
| Wage                 | - -         |           | 0.4947*** | 0.3614*** |
|                      | - -         |           | 0.0481    | 0.1623    |
| F statistic-FS       | 92.61       | 5.38      |           |
| N                    | 75972       | 75972     |           |
| Market fixed effects | Yes         | Yes       | Yes       | Yes       | Yes       |
| Firm fixed effects   | No          | Yes       | No        | Yes       | No        | Yes       |

Note: Labor supply elasticity results for unskilled workers. The first two columns show the results for the First Stage in which different sets of instruments are used for wage per worker, the third and fourth column the OLS point estimates, and the fifth and sixth columns the IV point estimates. Even columns estimate the labor supply elasticity within firms. Standard errors are clustered at the firm level. A Market is defined as an industry, region, year unit. *p<0.1, **p<0.05, ***p<0.01.

the analysis into skilled and unskilled workers. The last four columns of table 9 suggest that labor supply is relatively more elastic for unskilled workers in the manufacturing sector. This result strikes us as remarkable since, a priori, one would expect frictions in labor markets to affect unskilled workers more strongly. One explanation could be found in the theory of monopsony and minimum wages, as we discuss in the following subsection.

Our estimates of the wage elasticities of labor supply to the firm are an order of magnitude higher than other papers but still reject the assumption of perfect competition in labor markets. The previous literature can be divided into two strands. A small literature has used natural experiments in specific labor markets following a reduced-form approach. Falch (2010) finds an elasticity of 1.4 for school teachers in Norway. Staiger et al. (2010) find an elasticity of 0.1 for nurses in the U.S.24 Another set of papers use a more structural approach based on the dynamic monopsony model of Manning (2003a). Ransom and Sims (2010) find an elasticity of about 3.7 for public school teachers in Missouri. Ransom and Oaxaca (2010) analyze a grocery retailer in the U.S. and their estimates range from 1.5 to 3.0

24This result is at odds with Matsudaira (2014) who finds a perfectly elastic labor supply curve for low-wage nurse aides.
Figure 3: Distribution of labor supply elasticity to the individual firm

Note: This figure shows the distribution of labor supply elasticities across firms for the pool of workers, skilled and unskilled workers. The median elasticity is 2.74 for pooled workers, 1.86 for skilled workers, and 4.00 for unskilled workers.

(1.5-2.5 for women and 2.4-3 for men). Hirsch et al. (2010) estimate elasticities in the range of 2-4 across a wide range of jobs and employers using linked employer-employee data from Germany. Bachmann and Frings (2017) report elasticities in the range of 1.3-3.3 for manufacturing firms in Germany. Webber (2015) estimates an average labor supply elasticity to U.S. manufacturing firms of 1.82. In that paper, manufacturing is the sector that enjoys the least wage-setting power.

Finally, two recent papers estimate labor supply elasticities using quasi-experimental evidence: Kline et al. (2017) use patents applications to estimate labor supply elasticities finding that workers capture 29 cents of every dollar of patent-induced operating surplus; and Garin and Silverio (2017) uses exogenous shocks to exports in Portugal, finding that the rent shared by firms to workers was reduced in 1.5% after the great recession.

4.2.1 Labor supply elasticity and the minimum wage in Colombia

As highlighted above, our estimates suggest that the labor supply is relatively more elastic for lower-skilled workers in Colombia, a result that is at odds with what one would a priori expect. In this subsection, we argue that this result could indeed be rationalized by the presence of a binding minimum wage. We also provide empirical evidence consistent
Table 9: Labor Supply Elasticity by Industry

|                        | Pool of workers |                                          | Unskilled workers |                                          | Skilled workers |                                          |
|------------------------|-----------------|--------------------------------------------|-------------------|--------------------------------------------|----------------|--------------------------------------------|
|                        | Market FE       | Firm FE                                   | Market FE         | Firm FE                                   | Market FE       | Firm FE                                   |
| All industries         | 2.74            | 7.62                                      | 4.00              | 9.25                                      | 1.86           | 3.31                                      |
| Std. Dev.              | 0.082           | 0.043                                     | 0.051             | 0.028                                     | 0.141          | 0.121                                     |
| Food products and Beverages | 2.78        | 7.73                                      | 4.08              | 9.45                                      | 1.74           | 3.11                                      |
| Tobacco products       | 1.57            | 4.38                                      | 2.45              | 5.68                                      | 1.13           | 2.01                                      |
| Textiles               | 2.80            | 7.78                                      | 4.03              | 9.34                                      | 2.07           | 3.68                                      |
| Apparel                | 2.20            | 6.12                                      | 3.43              | 7.93                                      | 1.49           | 2.65                                      |
| Leather and leather products | 2.10        | 5.84                                      | 3.38              | 7.81                                      | 1.28           | 2.28                                      |
| Wood, cork, and straw products | 2.36        | 6.56                                      | 3.75              | 8.68                                      | 1.51           | 2.70                                      |
| Paper and paper products | 3.23         | 8.99                                      | 4.42              | 10.24                                     | 2.44           | 4.35                                      |
| Publishing, printing and media | 3.00        | 8.34                                      | 4.34              | 10.04                                     | 1.83           | 3.27                                      |
| Chemicals              | 3.71            | 10.37                                     | 4.28              | 9.92                                      | 2.60           | 4.64                                      |
| Rubber and plastic     | 3.00            | 8.35                                      | 4.23              | 9.80                                      | 2.14           | 3.81                                      |
| Non-metallic mineral products | 2.80        | 7.79                                      | 4.03              | 9.33                                      | 2.18           | 3.89                                      |
| Basic metals           | 2.96            | 8.22                                      | 4.35              | 10.06                                     | 2.13           | 3.79                                      |
| Fabricated metal products | 2.87         | 7.97                                      | 4.24              | 9.83                                      | 1.93           | 3.44                                      |
| Machinery and equipment| 2.90            | 8.06                                      | 4.20              | 9.73                                      | 1.92           | 3.41                                      |
| Computing Machinery    | 3.20            | 8.88                                      | 4.54              | 10.51                                     | 1.88           | 3.34                                      |
| Electrical machinery and apparatus | 3.09   | 8.60                                      | 4.08              | 9.44                                      | 2.16           | 3.84                                      |
| TV and communication equipment | 2.03     | 5.65                                      | 2.93              | 6.79                                      | 1.23           | 2.19                                      |
| Medical instruments    | 2.84            | 7.89                                      | 4.00              | 9.25                                      | 1.91           | 3.40                                      |
| Motor vehicles and trailers | 2.66         | 7.38                                      | 3.94              | 9.13                                      | 1.78           | 3.16                                      |
| Other transport equipment | 2.68          | 7.44                                      | 3.80              | 8.80                                      | 1.64           | 2.92                                      |
| Furniture              | 2.39            | 6.66                                      | 3.71              | 8.58                                      | 1.50           | 2.68                                      |

Note: This table shows median labor supply elasticities by 2-digit industry.

with this hypothesis.

The key observation for our argument is that, under the standard monopsonistic model of labor supply, the introduction of a binding minimum wage policy generates more (or perfectly) elastic labor supply curves in some range of workers’ wages which, in turn, attenuates the coefficient estimated in equation (10). We illustrate this point in Figures 4 and 5, where we plot the dynamics of our empirical strategy for a firm in the case where the minimum wage is binding and non binding, respectively. When the minimum wage is binding (Figure 4), the labor supply elasticity that we estimate corresponds to the slope of the orange segment connecting the equilibrium points B and C. However, when the minimum wage is non binding (Figure 5), the labor supply elasticity that we estimate corresponds to the slope of the blue segment using equilibrium points A and B. In the former case, the estimated labor supply curve is flatter (i.e., more elastic).25

25Labor unions are another type of institution that could affect the labor supply curve in a similar way as the minimum wage. In a monopsonistic market, labor unions’ bargaining for higher wages can create a horizontal labor supply curve and, as a result, capture rents from employers. Although the Colombian labor legislation recognizes unions as a part of the labor relations system, its role in wage-setting matters is nowadays minimal and essentially restricted to collective bargaining at the firm-level (Agudelo and Sala, 2015). Moreover, union density in Colombia is around 4% and the coverage of collective bargaining agreements is less than 2%. Thus, we believe that this channel is less likely to be driving our results.
The combination of the previous observation and the fact that minimum wages are typically more binding for lower-skilled workers, suggest that the estimated labor supply curve will be more elastic for this group of workers. We next argue that this seems to be the case in the manufacturing sector in Colombia. To that end, we briefly describe the minimum wage in Colombia and we provide some evidence consistent with our hypothesis.

Colombia has a uniform minimum wage that is adjusted on a yearly basis by a centralized bargaining process between representatives of labor unions, businesses, and the government. By law, the minimum wage should be raised to reflect the central bank inflation target for the year plus productivity changes. Since 1999, the Constitution further stipulates that yearly adjustments in the minimum wage should at least match past year’s inflation. As a result, the minimum wage has increased 21% in real terms between 1998 and 2010 (Joumard and Londono-Vélez, 2013). Compared to other economies, the minimum wage is set relatively high in Colombia. In 2011, the minimum wage stood at 71% of the average wage, one of the highest in the world, up from 58% in 2007. Moreover, the minimum wage is particularly binding in the poorest, low-productivity regions, where its level is above median and average income and where informality is also most prevalent (Joumard and Londono-Vélez, 2013).
Figure 5: Non Binding Minimum Wage

Note: This figure shows the dynamics of our identification strategy in the presence of a minimum wage. In this case the minimum wage is not binding and, thus, the labor supply elasticity that we estimate corresponds to the slope of the blue line.

Related to our analysis, the minimum wage also seems to bind more strongly for lower-skilled workers in the manufacturing sector. In Figure 6, we plot the distribution of average monthly (log) wage per worker reported by plants in the EAM survey over the period of analysis. Each panel shows the year-specific distribution of lower-skilled production workers, higher-skilled production workers, and administrative non-production workers. The vertical dashed lines denote one and two (log) minimum wages of the corresponding year. In the case of lower-skilled workers, the wage distribution is less dispersed and closer to the minimum wage, compared to the distribution of higher-skilled and administrative workers which is shifted to the right and much more disperse. Moreover, a big mass of lower-skilled workers falls between one and two minimum wages. Hence, we believe that in a counterfactual world without minimum wages this distribution would be more disperse and skewed to the left. We interpret this result as suggestive evidence that, in the manufacturing sector, the minimum wage mainly affects lower-skilled workers.

Finally, we develop an empirical test to formalize our hypothesis that labor supply elasticities should be higher for firms more constrained by a minimum wage policy. Our test is based on the estimation of the following equation:

$$\ln s_{it} = \beta_0 + \beta_1 \ln w_{it} + \beta_2 \ln w_{it} \cdot 1\{\text{Binding}_{it}\} + \gamma_{m(i,t)} + \epsilon_{it}$$

(12)
Figure 6: Distribution of average monthly (log) wage per worker in the manufacturing sector in Colombia, 2004-2012

Note: This figure plots the distribution of average monthly (log) wage per worker reported by plants in the EAM survey over the period 2004-2012. Each panel shows the year-specific distribution of low-skilled production workers, high-skilled production workers, and administrative non-production workers. The vertical dashed lines denote one and two (log) minimum wages of the corresponding year.

where $1\{\text{Binding}_{it}\}$ is an indicator function that takes the value of 1 if the minimum wage binds for firm $i$ at year $t$, and 0 otherwise. Since we do not observe individual wages, we construct the following measure to categorize firms affected by the minimum wage: $r_{it} = \frac{w_{it}^{\text{min}}}{\bar{w}_{it}}$, where $w_{it}^{\text{min}}$ is the statutory monthly minimum wage in Colombia and $\bar{w}_{it}$ is the average wage per worker. This ratio takes the value of 1 for firms paying the minimum wage to their workforce. As this ratio increases from 0 to 1, it is more likely that a firm is constrained by a minimum wage policy. Without loss of generality, we fix the control group of non-constrained firms to those with $r_{it} < 40\%$ (so that $1\{\text{Binding}_{it}\} = 0$). Alternatively, we define the group of affected firms as those with the ratio above a moving threshold $\delta$ (so that $1\{\text{Binding}_{it}\} = 1$). For example, $r_{it} \geq 60\%$. We then estimate equation (12) for different values of $\delta \in \{60\%, 65\%, 70\%, 75\%, 80\%, 85\%, 90\%\}$. 

Electronic copy available at: https://ssrn.com/abstract=3098141
If our hypothesis is right, then the coefficient $\beta_2$ should be positive and increasing over the range of $\delta$. That is, the labor supply becomes relatively more elastic for firms for which the minimum wage binds more strongly relative to firms unaffected by the policy (those with $r_{it} < 40\%$).\textsuperscript{26}

Figure 7 summarizes the results of our exercise by plotting the estimated coefficient $\beta_2$ across the different thresholds $\delta$. For reference, the horizontal orange line denotes the labor supply elasticity for the group of firms unaffected by the minimum wage (i.e., the coefficient $\beta_1$ from equation (12)). It is observed that, consistent with our hypothesis, the point estimate is positive and increasing as we get closer to 100%. For instance, when the threshold is 60%, the point estimate takes a value of 7.8, which means that the labor supply is 7.8 percentage points more elastic for firms with $r_{it} \geq 60\%$ than firms with $r_{it} < 40\%$. When the threshold is 90%, the point estimate takes a value above 20, corresponding to a highly elastic labor supply curve.

\textsuperscript{26}This exercise is robust to different thresholds different than 40%.
Our result suggests that firms more constrained by a minimum wage face more elastic labor supply curves, as predicted by a very simple theory of imperfect labor markets and minimum wages (Figures 4 and 5). Taken together, Figures 6 and 7 suggest that minimum wage policies provide a compelling explanation to our finding that labor supply elasticities are higher for lower-skilled workers. This result has also important policy implications for the labor market. Leaving aside unemployment effects, the minimum wage could indeed be working as a price floor that limits the wage-setting power of firms against lower-skilled production workers in the manufacturing sector.

Furthermore, a binding minimum wage also limits the incidence of payroll taxes as employers cannot pass-through labor costs to employees as lower wages (Lee and Saez, 2012). In this context, other labor market policies, such as payroll tax cuts, can be pretty effective in boosting formal employment as shown by Kugler et al. (2017), who explore the effects of a payroll tax cut implemented in Colombia at the end of 2012. Moreover, Lee and Saez (2012) show theoretically that under a binding minimum wage, a payroll tax cut for low-skilled workers is a Pareto improving policy.27

Finally, it is important to note that when the minimum wage $w_{it}^{min}$ is binding, the affected firms take the wage as given, and our measure of market power will only reflect pure markups. That is, the first order condition (2) from our minimization problem simplifies to $w_{it}^{min} = \lambda_{it} \times \partial Q_{it}(\cdot) / \partial L_{it}$, and rearranging terms we get to $MU_{it} = \delta_{it} / \alpha_{it}$.28 In this case, the minimum wage limits labor market power and the only source of market power that employers can exploit is the one in product markets. In the next section we proceed to disentangle our combined measure of market power into product and labor market power.

### 4.3 Plant-level markdowns and markups

The point estimates from the previous section suggest that there is a non-negligible degree of market power in labor markets. Using equation (5) we can translate the labor supply elasticities into markdowns, $MD_{it} = \epsilon_{it}^{lw} / (\epsilon_{it}^{lw} + 1)$. Column (3) in Table 10 reports a median markdown of 0.89 for the pool of workers. This estimate suggests that manufacturing workers are paid a wage that is 11 percent lower than their marginal revenue product

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27 These authors argue that even in a world with competitive labor markets, a minimum wage could be a welfare-improving policy if the government values redistribution from high- to low-wage workers and there is “efficient rationing”. That is, the workers who involuntarily lose their low-skilled jobs due to the minimum wage are those with the least surplus from working in the low-skilled sector.

28 This is another strategy that we could use to disentangle the degree of market power in product and labor markets, and is subject of future research.
(MRPL). Column (4) and (5) show substantial heterogeneity of markdowns across worker types. Unskilled workers are paid 90% of MRPL, and skilled workers 77% of MRPL. Although wage setting typically takes place at the sectoral level, we do not find too much variation of elasticities across industries.29

Finally, from equation (4) we can back out markups as \( MU_{it} = MP_{it} \times MD_{it} \). Table 10 column (2) displays a median markup of 1.78 for the Cobb-Douglas specification. This estimate suggests that in the Colombian manufacturing sector prices are 78 percent higher than marginal cost. There is also more variation in markups across industries than markdowns. Although both markets exhibit imperfect competition, it seems that the source of variation across industries is determined by the ease of firms to set prices above marginal costs. In the rest of this section we study the relationship between product and labor market power, and provide potential channels based on the literature of agglomeration that may explain our results.

Table 10: Imperfect Competition in Product and Labor Markets - Summary Statistics

|                         | (1)  | (2)  | (3)  | (4)  | (5)  |
|-------------------------|------|------|------|------|------|
|                         | MP   | MU   | MD   | MD   |      |
| All industries          | 2.02 | 1.78 | 0.89 | 0.90 | 0.77 |
| Food products and Beverages | 2.09 | 1.83 | 0.89 | 0.91 | 0.76 |
| Textiles                | 1.82 | 1.62 | 0.89 | 0.91 | 0.80 |
| Apparel                 | 1.96 | 1.68 | 0.86 | 0.89 | 0.73 |
| Leather and leather products | 2.04 | 1.75 | 0.86 | 0.89 | 0.71 |
| Wood, cork, and straw products | 1.94 | 1.68 | 0.87 | 0.90 | 0.72 |
| Paper and paper products | 2.27 | 2.01 | 0.90 | 0.91 | 0.82 |
| Publishing, printing and media | 2.21 | 1.98 | 0.90 | 0.91 | 0.77 |
| Rubber and plastic      | 1.93 | 1.72 | 0.90 | 0.91 | 0.80 |
| Basic metals            | 2.07 | 1.82 | 0.89 | 0.91 | 0.80 |
| Fabricated metal products | 1.98 | 1.76 | 0.89 | 0.91 | 0.79 |
| Machinery and equipment | 2.03 | 1.79 | 0.89 | 0.90 | 0.78 |
| Electrical machinery and apparatus | 2.04 | 1.82 | 0.90 | 0.91 | 0.80 |
| Medical instruments     | 1.91 | 1.66 | 0.89 | 0.90 | 0.77 |
| Motor vehicles and trailers | 2.03 | 1.78 | 0.89 | 0.90 | 0.77 |
| Other transport equipment | 2.03 | 1.75 | 0.88 | 0.90 | 0.75 |
| Furniture               | 2.03 | 1.77 | 0.87 | 0.90 | 0.74 |

Note: This table reports the median of our different measures of market power by industry. Column 1 reports CD measures of market power, column 2 markups, column 3 markdowns for the pool of workers, column 4 markdowns for unskilled workers, and column 5 for skilled workers. For consistency, the industries not included in the market power estimation are left out of the analysis (see the note of table 5).

Figure 8 shows a non-parametric relationship between markups and markdowns for different specifications. We conclude that there is a positive relationship between markups and markdowns implying that firms who exert more market power in product markets share more rents with their workers. In other words, there is a negative relationship between

29This result may be driven by the fact that we estimate labor coefficients that do not vary across sectors.
product and labor market power. At first, this result can be surprising, since one would expect a positive relationship of market power in both markets. However, there are potential explanations for this pattern based on the literature of productivity and agglomeration (Manning, 2010).

**Figure 8: Correlation of Markups and Markdowns**

Note: This figure shows the correlation between markups and markdowns. MU-CD stands for markups estimated using the output elasticity of labor from the Cobb-Douglas specification. MU-TL stands for markups estimated using the output elasticity of labor from the Translog specification.

For instance, low productive firms survive more in environments in which they exert more market power in product or labor markets. Thus, low productive firms sort into small markets in which there are more labor frictions and it is harder for workers to move across firms. In other words, workers enjoy better amenities and have more job opportunities in larger markets in which firms have less market power to set wages. This hypothesis is tested by Manning (2010) who finds that firms located in small villages are less productive and face more inelastic labor supply curves.

Figure 9 relates our measures of market power with labor market size finding that there is a positive relationship between markdowns and market size. As stated by Manning, “all labour markets are monopsonistic but less so in agglomerations”. Moreover, panel B of
Figure 9 shows a positive relationship between *markups* and market size which confirms the point emphasized by the agglomeration literature. Basically, that larger firms sort into more productive locations obtaining gains from the external Marshallian forces in big cities but at the expense of some market power. Therefore, this hypothesis could rationalize our finding of a negative correlation between market power in product vs. labor markets.

![Figure 9: Market Power and Market Size](https://ssrn.com/abstract=3098141)

Note: This figure relates the measures of market power with labor market size computed as the log of number of workers in 3 digit isic-sector-region-year cells. The figure documents that there is a positive relationship between *markdowns* and market size, this means that labor market power is higher in smaller places. On the other hand, there is a positive relationship between *markups* and market size.

### 4.4 Market power and plant characteristics

We now turn to explore correlations between market power and plant characteristics.\(^{30}\) We also take a step forward compared to what other people have done before and we further decompose these correlations into *markups* and *markdowns*. We run reduced-form regressions of the following form:

\[
\ln \mu_{jit} = \gamma_1 X_{jit} + \phi_j + \phi_t + \epsilon_{it}
\]

where \(\mu\) can be either plant-level market power, *markup*, or *markdown*, \(X\) is a set of plant characteristics that vary across specifications as described below, \(\phi_j\) are industry fixed ef-

\(^{30}\)This correlation exercise is frequently done in the IO and trade literature, see for instance DeLoecker and Warzynski (2012). We acknowledge that the correlations presented in this section are not necessarily causal and that they may be explained by time-varying unobserved heterogeneity across firms. However, we still find this exercise interesting and informative.
fects, $\phi_t$ are year fixed effects that control for aggregate shocks, and $\epsilon$ is a random error term. We consider the following set of plant characteristics: plant size, total factor productivity, value added per worker, exporter status, importer status, and the ratio between skilled and unskilled workers. Table 11 reports the results for this exercise. Column (1) displays the $\gamma_1$ point estimates for the combined measure of market power, column (2) for markups, and column (3) for markdowns.\(^{31}\)

Table 11: Market Power and Plant Characteristics

|                     | MP (1) | MU (2) | MD (3) |
|---------------------|--------|--------|--------|
| Size (log sales)    | 0.0668 | 0.1026 | 0.0150 |
|                     | (0.008) | (0.009) | (0.00008) |
| TFP (logs)          | 0.0660 | 0.7878 | -0.0032 |
|                     | (0.004) | (0.004) | (0.00006) |
| VA per worker (logs)| 0.1889 | 0.3026 | 0.0225 |
|                     | (0.001) | (0.002) | (0.0001) |
| Exporter            | 0.0466 | 0.1169 | 0.0310 |
|                     | (0.003) | (0.004) | (0.0004) |
| Importer            | 0.1097 | 0.1519 | 0.0338 |
|                     | (0.004) | (0.005) | (0.0004) |
| Skilled/Unskilled   | -0.0055 | -0.0083 | 0.0051 |
|                     | (0.0016) | (0.0019) | (0.0001) |
| Observations        | 43,666 | 43,666 | 77,120 |

Note: This table shows the coefficients from a regression between the log of market power and different plant characteristics. MP: combined market power, MU: markups, MD: markdowns. Each entry corresponds to a separate regression. All the specifications include industry and year effects. Standard errors are clustered at the plant level.

The results show a positive correlation between our combined measure of market power and plant size. For example, market power increases by 0.6% as sales increase by 10%. We proceed to decompose this result into markups and markdowns finding a positive correlation between firm size and product market power and a negative relationship with labor market power. For instance, for a 10% increase in sales, markups increase by 1% and markdowns increase by 0.1%. For the other firm characteristics, we obtain similar results: there is a positive correlation between our combined measure of market power and markups with value

\(^{31}\)Note that a higher markdown associates with lower labor market power.
added per worker, and exporter and importer status. However, there is a negative correlation between these measures and labor market power. In the next section, we explore the relationship of market power with market concentration and total factor productivity.

5 Market power, concentration, and productivity

5.1 Market power and concentration

This section correlates our market power measures with indexes of industry concentration. We construct Herfindahl indexes at the 3 digit ISIC level for each year using the eight biggest firms within industries in terms of sales. Intuitively, if more productive firms charge higher markups and markets are more concentrated with the presence of superstar firms, there should be a positive relationship between aggregate market power and the Herfindahl index.

We test this hypothesis in Figure 10 by plotting the Herfindahl index on the y-axis against our three measures of market power in the x-axis.\textsuperscript{32} Panel (a) shows a positive relationship between market concentration and aggregate market power at the industry level. In particular, a 1% increase in average market power is associated with a 0.63 p.p. increase in the Herfindahl index. Panel (b) also displays a positive relationship between average markups within industries and concentration. A 1% increase in markups is associated with a 0.60 p.p. increase in the Herfindahl index. Finally, panel (c) reports a weak positive (but not significant) correlation between market concentration and average markdowns.

Hence, the results suggest that the positive association between market concentration and aggregate market power is entirely explained by markups. One potential explanation is that industries more concentrated are dominated by superstar firms that charge higher markups in the product market and do not extract rents from their workers differently than less concentrated industries.

5.2 Market power and productivity

This section correlates market power measures with total factor productivity and explores the implications of market power distortion on resource misallocation. We start by testing the hypothesis that market power correlates positively with total factor productivity across

\textsuperscript{32}The unit of observation corresponds to ISIC 3 digit industries. We plot the mean for each industry across the period of analysis 2002-2012.
Figure 10: Market Power and Market Concentration

Note: This figure relates market concentration to our measures of market power: combined market power (top), markups (middle), and markdowns (bottom). Market concentration is measured by the Herfindahl index using the eight largest firms in each industry.
and within industries. We use value added per worker as a proxy for the productivity of firms.

In Figure 11 we analyze the relationship between market power and productivity. In panel (a) we exploit the variation across 3-digit industries. There is a positive relationship between the average market power and productivity. For instance, a 1% increase in average market power is associated with a 1.3% increase in productivity. In panel (b) we exploit the variation across firms within sectors and find a similar result, namely, that higher levels of market power are positively correlated with higher levels of productivity in every manufacturing sector.

In Figures 12 and 13 we break the previous results by markups and markdowns, respectively. In the case of markups, we find a similar result: a positive correlation between market power in product markets and productivity across sectors, and across firms within the same sector. However, in the case of labor market power there is a negative relationship with productivity across sectors and across firms within the same sector. The results suggest that more productive firms and industries charge higher markups and set markdowns closer to 1. One explanation could be that, when a firm is more productive, marginal costs are lower and by charging similar prices than their competitors they end up having higher markups. At the same time, this higher product market power allows them to pay a fairer share to their workforce and, thus, wages are closer to the marginal revenue product of labor.

5.3 Resource misallocation

In this section, we provide an application of our framework by exploring the relationship between market power and allocative efficiency. Recent research has emphasized the role of market power dispersion on the functioning of input markets. In particular, Banerjee and Duflo (2005) and Hsieh and Klenow (2009) suggest that the dispersion in firms’ marginal revenue works as a sufficient statistic for the functioning on input markets such as labor, capital, or intermediate inputs, and it may have important implications for resource misallocation and aggregate outcomes. One of the factors that determines marginal revenue dispersion is variable market power (i.e., the fact that firms in the same industry exert different levels of market power).

The main idea is that firms with higher market power than the average within the same sector produce less than the socially efficient output, while firms with lower market power
Figure 11: Productivity and Market Power

Note: This figure relates log market power (x-axis) with log productivity (y-axis). Productivity is measured by value added per worker. In panel (a) we report results taking averages at the 3 digit ISIC level and exploiting variation across industries. In panel (b) we first take the average of both variables across years for each firm and then plot the resulting relationship within the same sector.
Figure 12: Productivity and Markups

Note: This figure relates log markups (x-axis) with log productivity (y-axis). Productivity is measured by value added per worker. In panel (a) we report results taking averages at the 3 digit ISIC level and exploiting variation across industries. In panel (b) we first take the average of both variables across years for each firm and then plot the resulting relationship within the same sector.
Figure 13: Productivity and Markdowns

Note: This figure relates log markdowns (x-axis) with log productivity (y-axis). Productivity is measured by value added per worker. In panel (a) we report results taking averages at the 3 digit ISIC level and exploiting variation across industries. In panel (b) we first take the average of both variables across years for each firm and then plot the resulting relationship within the same sector.
produce more than the social optimum. In this sense, the measure that matters for the functioning of markets is the dispersion of market power rather than the level and this variation can come from two sources: *markups or markdowns*. Therefore, the goal of our application is to measure the relative TFP gains of eliminating variable market power in product markets vs. labor markets.

To that end, we estimate the implications of variable market power on TFP using the approach developed by HK. Although the analysis is similar to their paper, in the sense that variable market power is a distortion, our goal is not to measure the increase in TFP in a world with no economic distortions as they do. The idea, instead, consists of estimating the relative (static) TFP gains of eliminating variable *markups* vs. removing variable *markdowns*. In other words, the goal is to compare three different counterfactuals: 1) No market power distortion, 2) No *markup* distortion; and 3) No *markdown* distortion, such that we can decompose the total effect into *markups* and *markdowns*.

We start by assuming that aggregate sector output is a CES composite good, and each good is produced using two inputs: labor and capital. On the other hand, since labor is no longer perfectly substitutable across firms it also takes a CES expression. In particular, we can write, labor at the sector level as:

\[
L_s = \left( \sum_{i=1}^{M_s} \left( L_{si} \right)^{1+\beta} \right)^{\frac{\beta}{1+\beta}}
\]  

In the case in which *markups* and *markdowns* are constant across firms and in the absence of other economic distortions, the marginal revenue product of labor, MRPL, and capital, MRPK, over its marginal factor cost (MFCL and MFCK) should be equalized across firms. This implies that “revenue/cost productivity” defined as price times total factor productivity over its marginal factor cost should not vary across firms within the same industry. However, in the presence of economic distortions, such as variable market power, MRPL/MFCL or MRPK may differ across firms, diminishing TFP. HK provide an expression for TFP at the sector level that depends on economic distortions. We rewrite this expression in the case of variable market power in product and input markets. TFP in sector

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33 The analysis is similar in the sense that the variation that we use comes from \( w_i L_i / P_i Y_i \), which is the same variation that HK use to pin down economic distortions. We thank Marcela Eslava for pointing this out to us.

34 By static we mean holding entry, technology, and innovation constant.

35 This is an implication from the FOC of the firm optimization problem and factor price equalization.
s can be written as:

\[
TFP_s = \left[ \sum_{i=1}^{M_s} A_{si} \left( \frac{MD_{si}}{\mu_{si}} \right) \left( \frac{\sigma - 1}{\sigma + \beta} \right) \right]^{\frac{\sigma}{\sigma + \beta}}
\]

(15)

where \( s \) denotes a sector and \( i \) is a subindex for firms. The parameter \( M_s \) corresponds to the number of firms in sector \( s \), \( A_{si} \) captures productivity of firm \( i \), \( \sigma \) is the elasticity of substitution across varieties within the same industry, and \( \text{TFPR}_{si} \equiv P_{si} \cdot A_{si} \) is a parameter that captures revenue productivity and, at the social optimum, is equal for all the firms within the same industry. In our framework of variable markups and markdowns, we can express total revenue productivity over marginal factor cost at the firm level using the following equation:

\[
\text{TFPR}_{si} / \text{MFC}_{si} \propto \frac{MU_{si}}{MD_{si}^{\theta_{L,s}}}
\]

(16)

where \( MD_{si} \) corresponds to the markdown charged by firm \( i \) and \( MU_{si} \) to the markup.

HK showed that in the case of no distortions, \( TFP_s \) is maximized. For instance, consider the case in which firms’ productivity and market power is log normally distributed,

\[
(\ln A_{si}, \ln MD_{si}^{\theta_{L,s}} / MU_{si}) \sim \mathcal{N}(\mu_a, \mu_{MP}, \sigma^2_a, \sigma^2_{MP}, \sigma_{a,MP})
\]

Then, we can express total factor productivity as:

\[
\log TFP_s = \kappa - \left( \frac{\sigma \beta}{2(\sigma + \beta)} \right) \cdot \text{Var} \left( \frac{MD_{si}^{\theta_{L,s}}}{MU_{si}} \right)
\]

(17)

In the presence of variable market power, \( TFP_s \) decreases due to resource misallocation. From equation (17), it is easy to see that if there is more market power dispersion, the effect of resource misallocation on \( TFP \) is higher. The effect of this dispersion on \( TFP \) depends on the value of \( \sigma \) and \( \beta \). For instance, for a fixed value of \( \sigma \), the effect of variable market power on resource misallocation is actually lower than in the standard case when \( \beta \to \infty \). The intuition for this result is that labor is no longer perfectly substitutable across firms. Therefore, when labor moves from one firm to another, the gains in \( TFP \) are lower. Our

36In appendix D we derive all the expressions based on HK model.
goal is to estimate the relative gains of reducing market power dispersion in product vs. labor markets based on equation 15. To that end, we run three different counterfactuals:

1. Counterfactual with no market power dispersion

2. Counterfactual with no *markup* dispersion

3. Counterfactual with no *markdown* dispersion

This exercise relates to other studies that assessed the implications of different distortions on resource misallocation in the Colombian context. For example, Eslava et al. (2010) find that completely removing capital and labor adjustment frictions would yield a substantial increase in aggregate productivity in Colombia for the period 1982-1998. The increase in productivity arises because plants adjust labor and capital more efficiently, increasing the market share of more efficient plants and reducing the share of less efficient plants. Our paper contributes to this literature by considering another measure that reflects resource misallocation, the dispersion of market power.

Table 12 shows the results of our exercise. The unit of observation corresponds to 3-digit ISIC sectors. The first row reports summary statistics of eliminating the dispersion in the combined measure of market power within sectors in Colombia. On average, if we remove all variable market power TFP increases by 19.71% across sectors, the maximum increase is 49.3%, and the minimum is 6.8%.

| Counterfactual              | Mean | Std. Dev | Min  | Max  |
|----------------------------|------|----------|------|------|
| No MP dispersion           | 1.197| 0.093    | 1.068| 1.493|
| No MU dispersion           | 1.263| 0.124    | 1.067| 1.827|
| No MD dispersion           | 1.025| 0.011    | 1.005| 1.056|

Note: This table reports the average TFP gain across 3-digit ISIC sectors of eliminating market power dispersion using the approach developed by Hsieh and Klenow (2009). Row 1 eliminates market power dispersion, row 2 *markups* distortions, and row 3 *markdowns* distortions. The interpretation is as follows, for example, eliminating market power distortion increases TFP on average by 19.7%.

Likewise, the second row reports the results when we eliminate the dispersion of product market power within industries. On average, there is an increase of 26.3% in TFP across 3-digit ISIC industries. The reason why the gains are higher in eliminating *markup* distortions than market power distortions is due to the negative correlation between market

---

37 This is the same counterfactual ran by HK, but instead of calling it *markup* variation, they assume that firms within the same sector face different tax schedules.
power in product vs. labor markets. Finally, in the third row, we run the counterfactual of removing variable labor market power. On average, TFP increases by 2.5% across sectors. These results can be aggregated to the Colombian economy using a Cobb-Douglas or CES aggregator. We conclude that dispersion in product markets is more important than labor markets for TFP and that the negative correlation between markups and markdowns correct some of the economic distortions in the economy, for instance, the aggregate TFP increases by 7%.

To sum up, Figure 14 presents the distribution of TFP across sectors for the observed data (blue solid line) and the case in which we eliminate economic distortions (red dashed line). From this graph we conclude that eliminating variable market power, especially in product markets, may lead to significant increases in productivity. In a recent paper, Baqaee and Farhi (2017) ran a similar counterfactual for the US finding that TFP may increase by 40% after eliminating markup dispersion.

Figure 14: Distribution of total factor productivity (TFP) with variable Market Power

Note: This figure shows the distribution of total factor productivity (TFP) under variable (solid) and constant (dashed) market power. These distributions are constructed using equation (??). In the case of variable market power, we use the estimated measures of markups and markdowns. In the case of constant market power, we set these measures equal to the average of each industry.
6 Final Remarks

In this paper, we propose a simple methodology to disentangle firms’ market power in product and labor markets based on the method developed by DeLoecker and Warzynski (2012), a labor supply choice model, and plant level production data. In a nutshell, we first obtain a combined measure of market power at the plant level using production function “proxy” methods. Then we separate this metric into markups and markdowns by estimating labor supply elasticities to the individual firm instrumenting wages with the use of intermediate inputs. With these estimates in hand, we pin down markdowns, and then back out markups.

Our results confirm that product and labor markets (in the manufacturing sector) are not perfectly competitive, but the variation of combined market power across industries seems to be driven by the ease of firms to set prices above marginal costs. On average, manufacturing plants set prices 78% higher than marginal costs, and pay wages 11% lower than the marginal revenue product of labor. We also find a negative correlation between product and labor market power and more elastic labor supply curves for lower-skilled workers. For the last two results, we provide additional evidence for the mechanisms that could be at play. For example, we can rationalize the higher labor supply elasticity for lower-skilled workers by the presence of a minimum wage that binds more strongly for this group of workers. We also show that markups and markdowns are systematically related to industry and plant characteristics. There is a positive correlation between product market power and productivity, size, and exporter status, and a negative correlation between these measures and labor market power. We provide some potential explanations of these patterns based on the agglomeration literature on firm sorting, labor market power, and spatial economics.

We also show the utility of our framework with an application relevant to the misallocation literature where we measure the relative gains of removing market power dispersion using the approach developed by HK. We find that eliminating markup dispersion has more important implications on TFP than reducing markdown dispersion. Similarly, the negative correlation between market power in product vs. labor markets attenuates the economic distortion that market power has on TFP.
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A Output Elasticity Estimation

In this section we explain the method developed by ACF to estimate the output elasticity of variable inputs. The procedure consists of two steps. In the first step, the authors estimate a non-parametric function for value added, and, in a second step they use standard GMM techniques to identify the production function coefficients. Let’s consider a value added Translog production function:

\[ y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \epsilon_{it} \] (18)

where \( l \) is the log of labor, in this case the variable input, and \( k \) is the log of capital. For a Cobb Douglas production function we have \( \beta_{ll} = \beta_{kk} = \beta_{lk} = 0 \). In a first stage, ACF fit the following model

\[ y_{it} = \phi(l_{it}, k_{it}, m_{it}, z_{it}) + \epsilon_{it} \]

where \( \phi(\cdot) \) is a measure of expected output. ACF obtain estimates of expected output (\( \hat{\phi}_{it} \)) and an estimate for \( \epsilon_{it} \). Expected output is given by:

\[ \phi_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + h_{it}(m_{it}, k_{it}, z_{it}) \]

where \( m \) is the log of materials and energy. The second stage relies on the law of motion for productivity providing estimates for all coefficients of the production function,

\[ \omega_{it} = g_{it}(\omega_{it-1}) + \xi_{it} \]

\[ \omega_{it} = \gamma_{1i} \omega_{it-1} + \gamma_{2i} \omega_{it-1}^2 + \gamma_{3i} \omega_{it-1}^3 + \xi_{it} \]

After the first stage, ACF are able to compute the productivity level \( \omega_{it} \) for any value of the vector \( \beta = \{ \beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{lk} \} \). ACF can recover the innovation to productivity given \( \beta \),

---

38We also include in the production function estimation time fixed effects and 2 digit ISIC industry fixed effects.
39We include interaction of these variables and year dummy variables.
\( \xi_{it}(\beta) \), and form moments to obtain estimates of the production function,

\[
E \left[ \xi_{it}(\beta) \begin{pmatrix} l_{it-1} \\ k_{it} \\ l_{it-1}^2 \\ k_{it}^2 \\ l_{it-1}k_{it} \end{pmatrix} \right] = 0
\]

The authors use standard GMM techniques to estimate the production coefficients. Finally, one can use the estimated coefficients to construct the output elasticities. In the case of a Cobb Douglas and Translog production function the output-labor elasticity is given by:

\[
\hat{\theta}^{L_{cd}}_{it} = \hat{\beta}_l
\]

\[
\hat{\theta}^{L_{tl}}_{it} = \hat{\beta}_l + 2\hat{\beta}_{Il}l_{it} + \hat{\beta}_{Ik}k_{it}
\]

Finally, note that we do not observe the correct expenditure share for input \( X_{it} \) directly since we only observe actual revenue \( \tilde{Q}_{it} \equiv Q_{it} \exp(\epsilon_{it}) \). Therefore, one can use the residual \( \epsilon_{it} \) from the first stage to compute the corrected expenditure share for input \( X_{it} \) as follows

\[
\hat{\alpha}_{it} = \frac{p^X_{it}X_{it}}{p_{it}Q_{it} \exp(\epsilon_{it})}
\]

With all these ingredients it is possible to estimate market power for plant \( i \) at time \( t \).
B Hsieh-Klenow model with variable markups and markdowns

In this section we describe the model from Hsieh and Klenow (2009) and rewrite their main equations assuming exogenous variable markups and variable markdowns. Moreover, we derive an expression of total factor productivity as a function of the two sources of market power. We start by assuming that industry output in sector \( s \) is itself a CES composite good of differentiated products:

\[
Y_s = \sum_{i=1}^{M_s} \left( Y_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}
\]

where \( Y_{si} \) is a differentiated product and \( \sigma \) is the elasticity of substitution across varieties within sector \( s \). By the properties of CES, the price index in sector \( s \) is:

\[
P_s = \sum_{i=1}^{M_s} \left( P_{si}^{1-\sigma} \right)^{\frac{1}{1-\sigma}},
\]

where \( P_s \) is the standard CES price index, and \( P_{si} \) is the price of firm \( i \) in sector \( s \). We assume that the production function for each differentiated product is Cobb-Douglas with two inputs: labor and capital, and assume that there are constant returns to scale.

\[
Y_{si} = A_{si} K_{si}^{1-\theta_{ls}} L_{si}^{\theta_{ls}},
\]

where \( \theta_{ls} \) is the output elasticity with respect to labor. Using the FOC for capital and labor, we can write marginal revenue product of labor and capital and the price as:

\[
MRPL_{si} \equiv \theta_{ls} \cdot A_{si} \cdot \left( P_{si} Y_{si} L_{si} \right) = w \cdot \left( MU_{si} MD_{si} \right)
\]

\[
MRPK_{si} \equiv (1 - \theta_{ls}) A_{si} \cdot \left( P_{si} Y_{si} K_{si} \right) = R \cdot MU_{si}
\]

\[
P_{si} = \frac{1}{A_{si}} \left( \frac{R}{1 - \theta_{ls}} \right)^{1-\theta_{ls}} \left( \frac{w}{\theta_{ls}} \right)^{\theta_{ls}} \frac{MU_{si}}{MD_{si}^\theta_{ls}},
\]

where \( MU_{si} \) represents the markup and \( MD_{si} \) the markdown. Therefore, with constant market power, the marginal revenue product for both inputs should be equalized across firms within the same sector. Let’s define the average marginal revenue products in sector
Using the expressions above we can write total factor productivity in sector $s$ as:

$$
\frac{1}{MRPL_s} \equiv \frac{1}{\sum_{i=1}^{M_s} \frac{P_{si}Y_{si}}{MRPL_{si}}} P_{s}Y_{s} \\
= p_s^{\sigma-1} \sum_{i=1}^{M_s} \frac{1}{MRPL_{si}} \left( A_{si} \cdot \frac{MU_{si}}{MD_{si}} \right)^{\sigma-1} 
$$

(25)

$$
\frac{1}{MRPK_s} \equiv \frac{1}{\sum_{i=1}^{M_s} \frac{P_{si}Y_{si}}{MRPK_{si}}} P_{s}Y_{s} \\
= p_s^{\sigma-1} \sum_{i=1}^{M_s} \frac{1}{MRPK_{si}} \left( A_{si} \cdot \frac{MU_{si}}{MD_{si}} \right)^{\sigma-1} 
$$

(26)

Using equations 22 and 23 we can express

$$
L_{si} = \frac{\theta_{ls} P_{si}Y_{si}}{MRPL_{si}} \\
K_{si} = \frac{(1 - \theta_{ls}) P_{si}Y_{si}}{MRPK_{si}}
$$

Aggregating over all firms to solve for the labor hired in sector $s$

$$
L_s = \sum_{i=1}^{M_s} \left( \frac{\theta_{ls} \cdot P_{si}Y_{si}}{MRPL_{si}} \right) \\
= P_s Y_s \theta_{ls} \sum_{i=1}^{M_s} \left( \frac{1}{MRPL_{si}} \frac{P_{si}Y_{si}}{P_s Y_s} \right) \\
= \theta_{ls} P_s Y_s \frac{MRPL_s}{MRPL_s} 
$$

(30)

Aggregating over all firms to solve for the capital in sector $s$

$$
K_s = \sum_{i=1}^{M_s} \left( \frac{(1 - \theta_{ls}) \cdot P_{si}Y_{si}}{MRPK_{si}} \right) \\
= P_s Y_s (1 - \theta_{ls}) \sum_{i=1}^{M_s} \left( \frac{1}{MRPK_{si}} \frac{P_{si}Y_{si}}{P_s Y_s} \right) \\
= (1 - \theta_{ls}) P_s Y_s \frac{MRPK_s}{MRPK_s} 
$$

(33)

Using the expressions above we can write total factor productivity in sector $s$ as:

$$
TFP_s = \left( \frac{P_s Y_s}{L_s} \right)^{\theta_{ls}} \left( \frac{P_s Y_s}{K_s} \right)^{1-\theta_{ls}} \frac{1}{P_s} 
$$

(29)
Then TFP at the sector level is:

\[
TFP_s = \left( \frac{M\bar{R}PL_s}{\theta_{Ls}} \right)^{\theta_{Ls}} \left( \frac{M\bar{R}PK_s}{1 - \theta_{Ls}} \right)^{1-\theta_{Ls}} \frac{1}{P_s}
\]  

(36)

Finally using equations 26 and 28 we get that:

\[
TFP_s = \left[ p_s^{\gamma-1} \left( \frac{w \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left( \frac{MD_{si}}{MU_{si}} \right)^{\gamma} \theta_{Ls}}{1 - \theta_{Ls}} \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left( \frac{MD_{si}}{MU_{si}} \right)^{\gamma} \right)^{1-\theta_{Ls}} \right]^{-1} \left( \frac{1}{P_s} \right) 
\]  

(37)

Plugging in \( P_s \) from equation 20 we conclude that:

\[
TFP_s = \left[ \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left( \frac{MD_{si}^{\theta_{Ls}}}{MU_{si}} \right)^{\gamma-1} \right]^{\sigma-1} \left[ \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left( \frac{MD_{si}^{\theta_{Ls}}}{MU_{si}} \right)^{\sigma} \right]^{-1},
\]  

(38)

which is the expression that we use in the paper to measure the relative gains of eliminating market power dispersion in product vs. labor markets.