

Measuring Imperfect Competition in Product and Labor Markets. An Empirical Analysis using Firm-level Production Data ^{*}

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Abstract

In this paper, we develop a simple theoretical model that allows us to disentangle empirically the extent of imperfect competition in product and labor markets using plant-level production data. The model assumes profit-maximizing producers that face upward-sloping labor supply and downward-sloping product demand curves. We derive a reduced-form formula for the ratio between markdowns and markups based on [DeLoecker and Warzynski \(2012\)](#). We use production function estimation techniques to estimate output elasticities and construct a measure of combined market power. We separate product and labor market power by estimating firm-level labor supply elasticities instrumenting wages with intermediate inputs. Our results suggest that both markets exhibit imperfect competition, but variation across industries is driven by the ease of firms to set prices above marginal costs. On average, manufacturing plants charge prices 78% higher than marginal costs, and pay wages 11% less than marginal revenue productivity of labor. We find a negative correlation between product and labor market power and more elastic labor supply curves for unskilled workers. Moreover, we obtain a positive correlation between firms' product market power and productivity, size and exporter status, and a negative correlation of these measures with labor market power. In the last part, we estimate the relative gains of eliminating market power dispersion on allocative efficiency using the model by [Hsieh and Klenow \(2009\)](#). We find that market power dispersion in product markets is more important on TFP than labor markets, and that the negative correlation between the two measures of market power corrects in 7% the economic distortion derived from market power dispersion.

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1 Introduction

There has been a long interest in economics to estimate firm's market power. For instance, IO and trade economists have developed different techniques to measure market power at the firm level since they provide relevant information on different market outcomes (DeLoecker and Warzynski, 2012). Similarly, recent studies in labor economics have estimated firm's market power in labor since a monopsony model rationalizes different facts found recently by the employer-employee literature. For example, that wages of workers with similar skills differ across firms (Card et al., 2016). Moreover, according to some authors market power in labor may be even more important on aggregate outcomes than in product markets (Naidu et al., 2018).

However, the question of whether labor markets and product markets are “imperfectly competitive” has been typically approached separately for each market. Most of these studies have estimated markups, and very few have been interested in estimating markdowns.¹ The main reason is that it has been hard to find quasi-experimental evidence to estimate residual labor supply elasticities at the firm level.² The aim of this paper is to approach this question from a joint perspective and measure the extent of market power of firms in both product and labor markets using production-level data.³

To this end, we develop a simple model to estimate *markups* and *markdowns* using a unified framework.⁴ The model guides the empirical analysis of the paper, which is based on microdata from Colombian manufacturing plants and a rigorous identification strategy. In the first stage, we combine tools from Industrial Organization and Labor Economics to estimate market power and policy-relevant elasticities. The identification comes from different sources of variation using the richness of our data set. In a second stage, we seek to establish links between markups, markdowns, and firm characteristics.

Moreover, since a new literature has emphasized the role of market power dispersion on the functioning of input markets, in the last section, we proceed to estimate the relative gains of reducing market power dispersion in labor vs product markets using the model developed by Hsieh and Klenow (2009) (HK, hereafter).⁵

¹In a recent conference in which there was a discussion about the book “*Radical Markets*” by Eric Posner and Glen Weyl, Emanuel Saez pointed out that it is important to consider how policies that usually affect one side of the market, actually affect both sides. The example that he gave was labor unions.

²Nevertheless, some recent studies have estimated market power in labor, for example, Kline et al. (2017).

³The study that is closest to ours is (Dobbelaere and Mairesse, 2013) that categorize industries according to their market power in product and labor markets.

⁴In our paper we will refer to the markup as the gap between the price and the marginal cost, and we define the wage markdown as the gap between the wage and the marginal revenue product of labor.

⁵For example, in the misallocation literature there are important hypotheses that suggest that the dispersion

From a policy perspective, it is important to identify and measure the strength of market power in product and labor markets across sectors. Markups are a key element in drawing a picture of the competitiveness and profitability of an industry, as well as of the dispersion and inequality across plants. Markups help identify foci of entry barriers and reduced competition, as well as possibilities for firm growth and development. On the other hand, markdowns help identify foci of frictions that give employers monopsony power in labor markets, and explain the fact that workers with similar observable and unobservable characteristics are paid differently. Moreover, ignoring the existence of employer market power could lead to incorrect conclusions on the driving force behind changes in wage inequality (Manning, 2003b).

In the first part of the paper, we develop a partial equilibrium model in which cost-minimizing firms have market power in both, product and input markets. We extend the method of DeLoecker and Warzynski (2012) by assuming that firms face an upward-sloping labor supply as in Card et al. (2016). 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. In particular, the equation states that the ratio of product markups to labor markdowns (left hand side) is equal to the ratio of the output elasticity of labor and the share of labor costs in total output (right hand side). In addition, we define the ratio of markups to markdowns as the combined measure of market power in both markets. Intuitively, the right hand side of the equation suggests that firms enjoy 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 setting wages below the marginal product of labor (markdown).

In the second part, we propose different strategies to estimate the elements of our key 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 costs in total output, which is observable in any production data, allows us to compute the combined measure of market power.

To disentangle the parts corresponding to product and labor markets, we develop an empirical strategy to estimate markdowns using firm-level production data. We follow the model developed by Card et al. (2016) based on a Roy model in which workers have heterogeneous preferences for different workplaces. From the model, we get a reduced-form equation for the

of market power is associated with lower total factor productivity at the aggregate level.

relation between labor and wages that allows us to estimate the labor supply elasticity to the individual firm. Since this equation is endogenous by nature, we identify the coefficient of wages using intermediate inputs as an instrumental variable. Ideally, we would like to instrument wage per efficiency units with productivity shocks at the firm level. However, since TFP shocks are not observable, we take an old idea from the production function literature in which materials work as a proxy for TFP shocks. In that sense, our exclusion restriction implies that changes in the use of intermediate inputs within firms are associated with changes in TFP that shift the labor demand curve but not the labor supply curve to the firm.⁶

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 can back out markups through the main equation. It is important to note that our model is over-identified, in the sense that it is possible to follow alternative empirical strategies to estimate the same objects of interest. For instance, for single product firms, we can 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 identify the markdown.⁷ Additionally, we can use other instruments as well, for example, we can use the classic BLP instruments such as leave-out mean prices, inputs or wages in each industry. However, we believe that since we are using firm-level production data, it is much easier to define a labor market than a product market, in which foreign firms compete with domestic firms. Therefore, in principle, we only estimate labor supply elasticities.

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 enjoy higher or lower monopsony power.⁸ Additionally, we explore the systematic relation of markups and markdowns with plant characteristics. Namely, total factor productivity (TFP), plant size, and exporter status.

Finally, in the last part, we proceed to test some of the hypotheses pioneered by the misallocation literature. In particular [Banerjee and Duflo \(2005\)](#) and [Hsieh and Klenow \(2009\)](#) suggest that the dispersion in firm's marginal revenue works as a sufficient statistic to the functioning on inputs markets, such as labor, capital, or intermediate inputs, and it may have important

⁶Although 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.

⁷We leave exercises like this as a topic in our future research agenda.

⁸We think in terms of "monopsony" or "oligopsony" as employers having some wage-setting power.

implications on resource misallocation. Furthermore, one of the factors that could explain the dispersion in marginal revenue is given by variable market power (i.e. the fact that firms in the same industry enjoy different levels of market power). Therefore, we measure the relative gains in TFP of eliminating variable market power in product vs labor markets using the analytical structure developed by [Hsieh and Klenow \(2009\)](#).

For the empirical analysis, we use a panel of Colombian manufacturing plants 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 the ease of firms to set prices above marginal costs. That is, manufacturing firms enjoy 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 also 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 in play.⁹ When we correlate market power and firm characteristics, 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 \(2010\)](#) on firm sorting, labor market power, and spatial economics. In terms of resource misallocation, we show that the relative gain in TFP of reducing the dispersion of markups is more important than reducing the dispersion of markdowns. Taken together, in our exercise the economic distortion of variable market power on TFP is reduced by approximately 7% when it is eliminated.

In terms of the 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. In particular, our work is closely related to all the literature that extended the seminal work of [Hall \(1988\)](#) in different directions. On the product market side, we build on recent work by [DeLoecker and Warzynski \(2012\)](#) 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 enjoy market power and are heterogeneous.

On the labor market side, the article fits into the scarce literature that has attempted to

⁹For 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 that hire relatively more unskilled workers.

measure market power in labor markets (e.g., see [Manning \(2010\)](#) for a recent review). It is also related to a new literature that considers imperfect labor markets to explain the relationship between firms' productivity and wages ([Card et al., 2016](#)). For example, labor market power can explain the fact that "the dispersion of productivity across firms mirrors trends in wage inequality across workers". To the best of our knowledge, this is the first paper that estimates the elasticity of labor supply to the individual firm using BLP-type methods and intermediate inputs as instruments.

Finally, our work also speaks to recent research that has addressed product and labor market imperfections simultaneously based on Hall's approach ([Crépon et al., 2005](#); [Dobbelaere and Mairesse, 2013](#)). Both papers estimate production functions using GMM methods and lagged values of factor inputs as instruments. In particular, [Dobbelaere and Mairesse \(2013\)](#) estimate a parameter of joint market imperfections from the difference between output elasticities of labor and materials and their revenue shares.

Our study differentiates from previous work in important ways. First, we estimate production functions using the method of [Akerberg 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 as an instrumental variable, which lets us identify the elasticity of labor supply to the individual firm directly. Hence, by combining tools from IO and Labor literature we are able to estimate two equations in an over-identified setting, which imposes more discipline in the empirical estimates with respect 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.

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 in TFP and the misallocation of resources 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.¹⁰ Finally, the model and strategy here developed can be easily

¹⁰Importantly, 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. This point was formally made by [Lee and Saez](#)

adjusted and adopted in other countries with less-detailed production databases. In particular, we believe this is the first paper that estimates labor supply elasticities to the individual firm using materials as an instrumental variable for wages, a strategy that can be easily replicated in other countries.

The remainder of the paper is organized as follows. In section 2, we present our empirical strategy based on [DeLoecker and Warzynski \(2012\)](#) and [Card et al. \(2016\)](#). We divide this section into two parts. First, we explain the methodology for the production function estimation and, in the second part, our empirical strategy to estimate labor supply elasticities at the firm level. Both methodologies rely on the fact that the use of intermediate inputs is a good proxy for productivity shocks. Section 3 describes the database for our empirical application, a panel of Colombian manufacturing plants spanning the period 2002 to 2014. Section 4 reports our main results and characterizes firms and sectors in terms of product and labor market power. Finally, in section 5 we test the hypothesis that market power dispersion is associated with lower aggregate total factor productivity following [Hsieh and Klenow \(2009\)](#). Section 6 concludes.

2 Empirical Strategy

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

$$Q_{it} = Q_{it}(X_{it}^1, \dots, X_{it}^{V-1}, L_{it}, K_{it}, \omega_{it}) \quad (1)$$

where X_{it}^v corresponds to a variable input, V is the total number of variable input, L_{it} corresponds to labor, K_{it} to capital stock, and ω_{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 behave as a monopoly in the market of the good that produces, and as a monopsony in the labor market. Then, the associated Lagrangian corresponds to:

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

where P_{it}^v corresponds to the input price, the term r_{it} to the capital cost, and w_{it} to the wage [\(2012\)](#).

that the firm pays. The first order condition of this minimization problem with respect to any variable input can be written as:

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

where ϵ_{it}^{Lw} corresponds to the labor supply elasticity to the firm, and therefore, the term between parentheses is the inverse of markdown MD_{it} . The interpretation of this term is as follows: if wages at the firm level increases at 1%, there is an increase in the share of workers that are willing to work at this firm in $\epsilon_{it}^{Lw}\%$. By an envelope theorem argument λ_{it} is the marginal cost of producing one unit of output. Rearranging terms and using the fact that the marginal cost can be expressed as the ratio between prices and markups ($\lambda_{it} = \frac{P_{it}}{MU_{it}}$), where P_{it} is the price of one unit of output, and MU_{it} is the markup, then we express our combined measure of market power MP_{it} as:

$$MP_{it} = \frac{MU_{it}}{MD_{it}} = \frac{\theta_{it}^L}{\alpha_{it}^L} \quad (3)$$

where the parameter θ_{it}^L corresponds to the output elasticity with respect to labor, and α_{it}^L to the wage bill share on total revenue or value added. Equation (3) can be generalized for any variable input X_{it}^v . Therefore, our key equation that guides the empirical analysis can be described as follows:

$$MP_{it}^v = \frac{MU_{it}^v}{MD_{it}^v} = \frac{\theta_{it}^v}{\alpha_{it}^v} \quad (4)$$

where α_{it}^v is the share of a variable factor v (e.g. blue-collar workers) in total revenue and θ_{it}^v is the output-elasticity of factor v . Markdowns are defined as the gap between wage and marginal revenue product of labor, and markup is the gap between price and marginal cost. From the FOC of the firm's profit maximization problem we can also express markups and markdowns as:

$$MU_{it} = \frac{p_{it}}{mc_{it}} = \frac{|\epsilon_{it}^p|}{|\epsilon_{it}^p| - 1} \quad MD_{it} = \frac{w_{it}}{MRPL_{it}} = \frac{\epsilon_{it}^{Lw}}{\epsilon_{it}^{Lw} + 1} \quad (5)$$

where ϵ_{it}^p is the product-demand elasticity and ϵ_{it}^{Lw} is the elasticity of labor supply to the firm.¹¹ The first equation is some rearrangement of the Lerner index, while the second equation is its counterpart for monopsonies.

¹¹Based 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 has been termed the "rate of exploitation" (Hicks, 1932).

The degree of market power can be deduced as soon as α_{it}^v and θ_{it}^v are pinned down. Note that α_{it}^v is typically observed in the data. However, θ_{it}^v is a parameter that we need to estimate. However, there is an identification problem since market power is coming from two different sources. Therefore, to determine the source of market power, either ϵ_{it}^p or ϵ_{it}^{Lw} need to be estimated as well. Thus, our strategy consists of estimating market power using standard production function techniques and then estimate the labor supply elasticity to the individual firm to identify markdowns and then back out markups.

Several recent papers have estimated firm-level markups by focusing on the right hand side of equation (4) and implicitly assuming perfect competition in labor markets (e.g., see DeLoecker et al. (2016)).¹² 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 it is important to separate both measures in terms of different market outcomes, such as resource misallocation or inequality. 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 will be 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, in this case the source of imperfect competition comes from the labor market and not from the market of goods. With our proposed framework we would be able to separate these measures to identify both sources of market power variation at the firm and industry level.

2.1 Production function estimation

The estimation and identification of θ_{it}^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 Akerberg et al. (2015).¹³ This method is also used by DeLoecker and Warzynski (2012) who estimate

¹²In 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 to be affected 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 were affected by the trade liberalization episode so that their point estimates are not affected.

¹³OLS 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).

markups at the firm level. We adopt the same approach as [Akerberg 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 not a contribution of this paper, we refer the reader to Appendix C for more details on the 2-step method used to estimate the output elasticity of variable inputs. In practice, the implementation of this method requires making parametric assumptions about the functional form of the production function (equation 12). We follow [DeLoecker and Warzynski \(2012\)](#) and consider a Cobb-Douglas and a Translog specification:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \quad (6)$$

$$y_{it} = \beta_l l_{it} + \beta_{ll} l_{it}^2 + \beta_k k_{it} + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \eta_{it} \quad (7)$$

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 the aggregate market power into markups and markdowns we adopt a discrete choice method of the IO literature based on [Berry \(1994\)](#) to pin down price-demand elasticities or labor-supply elasticities. However, because we consider that is easier to define a labor market instead of a product market, we separate market power between product and labor markets estimating the labor supply elasticity.¹⁴ We define a labor market as region-year-sector. Our theoretical framework is based on the model developed by [Card et al. \(2016\)](#). In the next section we explain our empirical strategy to estimate labor supply elasticities in more detail.

2.2 Labor supply elasticity

We pin down markdowns by estimating the labor supply elasticity to the individual firm.¹⁵ 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 working

¹⁴As robustness check, we are also planning to estimate price-demand elasticities in the near future.

¹⁵Note 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.

at firm i is given by:

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

Assuming that ϵ_{nit} 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 at 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 proceed to estimate the following equation:

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

Note that we get rid off the denominator including a market fixed effect. Where ψ_i is a plant fixed effect and $\gamma_{m(i,t)}$ is a market fixed effect defined as a region-industry-year level. A simple OLS regression of equation (10) leads to a biased β 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, β , 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 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 imply a shift in the labor supply curve, an assumption we believe to be plausible in practice.¹⁶ Finally, the elasticity of the labor supply to the individual firm implied by the model is computed as:

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

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. However we believe that our preliminary results are consistent with the Bargaining literature in labor

¹⁶The greatest threat to our exclusion restriction is that certain labor supply shocks could also affect the use of intermediate inputs at the firm level.

markets. Finally, note that equation (10) can be estimated separately for different types of workers (i.e by skill groups). In the empirical section, we explore the heterogeneity by high-skilled and low-skilled workers.

3 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 workers. It provides standard plant survey information plus much more rare data on physical quantities and unit values of manufactured products and used inputs.¹⁷ 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 (namely, [Eslava et al. \(2004\)](#) and [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.¹⁸

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;¹⁹ we drop any year-plant 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

¹⁷The 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 fourth-digit level of the ISIC Revision 3.

¹⁸The use of industry-level deflators raises the issue of the possibility that prices may vary across firms. We are planning to 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).

¹⁹The key variables are: gross output, number of workers, wage bill, wage per worker, capital, intermediate inputs.

percentile 1 and 99. Our final sample contains 80,329 plant-year observations.²⁰

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 employee is twice as large for skilled than unskilled workers²¹ 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 2-digit industry is Food and Beverages, followed by Clothing, Chemicals, and Plastic products. Together 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 α_{it}^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 θ_{it}^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 in turn suggests that it is important 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 for the production function by industry.

4 Results

In this section we describe our empirical results. First, we estimate production functions to construct our combined measure of market power. Second, we estimate the elasticity of the labor supply to the individual firm and construct our plant-level markdowns. Finally, we use the two strategies to back out markups and correlate all these measures with plant characteristics.

²⁰The results are robust to a variety of different bounds for the winsorizing procedure and as a number of different strategies for dealing with outliers as well.

²¹Skilled workers are administrative and professional production workers, and unskilled workers are production workers without a professional degree.

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 at the plant level. 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.²² The last row of each panel reports the average returns to scale which are slightly higher than 1.²³

With these estimates at 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 a relatively recent strand that has estimated market power using the method proposed by DeLoecker and Warzynski (2012). These papers assume perfect competition in labor markets and thus interpret their 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 firms. 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

²²Note 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.

²³A similar result is reported in the paper by DeLoecker et al. (2016) where 68 percent of the sample exhibits increasing returns to scale.

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

4.2 Labor supply elasticity

In this section, we now 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 inputs used (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 that increases the use of intermediate inputs, labor demand shifts up and the number of workers hired by the firm increases. 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 or labor supply shocks are not correlated with the use of intermediate inputs.

Table 6 shows our 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 used (panel C).²⁴ In the second stage, we use the variation introduced by these instruments to identify the coefficient of interest β 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 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

²⁴This could be due to the fact that the number of inputs used 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.

are still similar in magnitude.²⁵

In Tables 7 and 8 we explore the heterogeneity of labor supply by separating the analysis into skilled and unskilled workers.²⁶ 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 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.

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 productivity shocks. 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.²⁷

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 market FE and firm FE specifications, with relatively little variation across sectors. However, There is more variation when we split 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.²⁸ Another set of papers use a more structural approach based on the dynamic

²⁵The estimation that uses the number of inputs as an instrument is meaningless because there is no first-stage.

²⁶We 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.

²⁷We choose the estimates that use materials because they present the highest precision (lower standard errors) compared to electricity and number of inputs used.

²⁸This result is at odds with Matsudaira (2014) who finds a perfectly elastic labor supply curve for low-wage nurse aides.

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 single grocery retailer in the U.S. and their estimates range from 1.5 to 3.0 (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 set 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](#) 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, low-skilled workers, and the minimum wage in Colombia

As highlighted above, our estimates suggest that the labor supply is relatively more elastic for low-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 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).²⁹

²⁹ Another important institution that could affect the labor supply curve in a similar way as the minimum wage, is the case of labor unions. 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%.

The combination of this observation and the fact that minimum wages are typically more binding for low-skilled workers, suggest that when one estimates the labor supply curve for this group of workers, it will be more elastic. We next argue that this seems to be the case for 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).

More importantly to our analysis, the minimum wage also seems to be binding for low-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 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. In the case of low-skilled workers, the wage distribution is less dispersed and closer to the minimum wage, compared to the distribution for high-skilled and administrative workers which is shifted to the right and much more disperse. Moreover, a big mass of low-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 low-skilled workers.

Finally, we develop an empirical test to formalize our hypothesis that labor supply elasticities should be higher for firms more constrained by the minimum wage policy. Our test is

Thus, we believe that this channel is less likely to be driving our results.

based on estimating the following equation:

$$\ln s_{it} = \beta_0 + \beta_1 \ln w_{it} + \beta_2 \ln w_{it} \cdot \mathbf{1}\{\text{Binding}_{it}\} + \gamma_{m(i,t)} + \epsilon_{it} \quad (12)$$

where $\mathbf{1}\{\text{Binding}_{it}\}$ 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, only average wages per worker, to categorize firms affected by the minimum wage, we construct the following measure: $r_{it} = w_t^{\min} / \bar{w}_{it}$, where w_t^{\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. Therefore, as this ratio increases from 0 to 1, it is more likely that a firm is constrained by a minimum wage policy. Accordingly, we define the group of affected firms as those with the ratio above a certain threshold δ , e.g. $r_{it} \geq 60\%$ (so that $\mathbf{1}\{\text{Binding}_{it}\} = 1$), and we fix the control group of non-constrained firms to those with $r_{it} < 40\%$ (so that $\mathbf{1}\{\text{Binding}_{it}\} = 0$). We then estimate equation (12) for the different values of $\delta \in \{60\%, 65\%, 70\%, 75\%, 80\%, 85\%, 90\%\}$.

If our hypothesis is right, then the coefficient β_2 should be positive and increasing over the range of δ . That is, the labor supply becomes relatively more elastic for firms for which the minimum wage binds relative to firms not constrained by a minimum wage policy (those with $r_{it} < 40\%$).³⁰

Figure 7 summarizes the results of our exercise by plotting the estimated coefficient β_2 across the different thresholds δ . For reference, the horizontal orange line denotes the labor supply elasticity for the group of firms not constrained by the minimum wage, i.e. the coefficient β_1 from equation (12). It is observed that, consistent with our hypothesis, the point estimate is positive and it increases 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, which suggests almost perfectly elastic labor supply curves.

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 low-skilled workers. This result has also important policy implications for the labor market.

³⁰This exercise is robust to different thresholds different than 40%.

Leaving aside unemployment effects, the minimum wage could indeed be working as a price floor that limits the wage-setting power of firms against low-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.

Finally, it is important to note that if the restriction of a minimum wage w_{it}^{min} is binding, then the affected firms take the wage as given, and our measure of market power only captures 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 we get to $MU_{it} = \theta_{it}^L / \alpha_{it}^L$.³¹ Hence, the minimum wage limits market power in labor markets 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 an average 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 the marginal revenue product they create (MRPL). Column (4) and (5) show substantial heterogeneity of markdowns across worker types. On average, unskilled workers are paid 90% of MRPL, and skilled workers 75% of MRPL. Although wage setting typically takes place at the sectoral level, we do not find too much variation of elasticities across industries.³²

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

³¹This 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.

³²This result is driven by the fact that we estimate labor coefficients that don't vary across sectors

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.

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 that have more market power in product markets share more rents with their workers. Or in other words, there is a negative relationship between product and labor market power. At first, this result can be striking, 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).

In particular, low productive firms can survive more in environments in which they enjoy more market power in product or labor markets. Thus, low productive firms sort in small markets in which there are more labor frictions and it is more difficult for workers to move across firms. Hence, the firm distribution in terms of size or productivity shifts to the left in small markets relative such as small cities or remote locations. 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 the 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 emphasised by the agglomeration literature. Basically, that larger firms sort into more productive locations, obtaining gains from the external Marshallian forces in big cities, but they sacrifice some market power. Therefore, this hypothesis could rationalize our finding of a negative correlation between market power in product vs labor markets.

4.4 Market power and plant characteristics

We now turn to explore correlations between market power and plant characteristics.³³ We also take a step forward compared to what other people have done before and we further decompose these correlations into its two components, markups and markdowns. We run reduced-form regressions of the following form:

$$\ln \mu_{jit} = \gamma_1 X_{jit} + \phi_j + \phi_t + \epsilon_{it} \quad (13)$$

where μ can be either plant-level market power, markup, or markdown, X is a set of plant characteristics that vary across specifications, further described below, ϕ_j are industry fixed effects, ϕ_t are year fixed effects that control for aggregate shocks, and ϵ 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 unskilled workers. Table 11 reports results for this exercise. Column (1) displays the γ_1 point estimates for the combined measure of market power, column (2) for markups and finally column (3) for markdowns.³⁴

From our results we infer that there is a positive correlation between our combined measure of market power and plant size. For example, a 10% increase in sales is associated with a 0.6% increase in market power. We proceed to decompose this result in markups and markdowns, we find a positive correlation of firm size with product market power and a negative correlation with labor market power. For instance, markups increase in 1% when sales increase in 10%, and markdowns increase in 0.1%. For the other firm characteristics we obtain similar results. In particular there is a positive correlation between our combined measure of market power and markups with value 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.

³³This 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.

³⁴A higher markdown is associated with less market power in labor markets.

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 super star firms, there should be a positive relation between aggregate market power measures and the Herfindahl index.

We test this hypothesis in Figure 10 by plotting the Herfindahl index on the y-axis against the log of the mean of market power in the x-axis.³⁵ Panel (a) suggests that there is a positive relationship between market concentration and aggregate measures of market power at the industry level. In particular, a 1% increase in the average of market power is associated with 0.63 p.p. increase in the Herfindahl index. We proceed to disentangle this correlation between markups and markdowns.

Similarly, panel (b) in the same figure plots the same relationship for the means of markups within industries instead of our combined measure of market power. We conclude that there is a positive relationship between these two variables. A 1% increase in markups is associated with a 0.60 p.p. increase in the Herfindahl index. One potential explanation is that industries more concentrated are dominated by super star firms that charge higher markups in the product market.

Finally, in panel (c) we correlate the Herfindahl index with the log mean of markdowns. There is a negative (but not significant) correlation between these two measures. This could be explained by the fact that more productive firms charge lower markdowns, therefore when markets are more concentrated by the presence of super star firms, average markdowns are lower.

5.2 Market power and productivity

This section correlates market power measures with total factor productivity and explore the implications of market power distortion on resource misallocation. We start by testing the hypothesis that higher market power correlates positively with total factor productivity across and within industries. Our measure of firm's productivity corresponds to value added per worker.

³⁵The unit of observation correspond to ISIC 3 digit industries. We plot the mean for each industry across the period of analysis 2002-2012.

In Figure 11, we explore the relationship between market power and productivity. In panel (a) we exploit the variation across 3-digit industries. It can be concluded that there is a positive relationship between average measure of market power and productivity. For instance, a 1% increase in average market power is associated with a 1.3% increase in productivity. On the other hand, in panel (b) we exploit the variation across firms within sectors, and find a similar result. Namely, that higher levels of market power are associated with higher levels of productivity in every manufacturing sector.

In Figures 12 and 13, we repeat this exercise but for markups and markdowns, respectively. In the case of markups we find a similar result. Basically, that there is a positive correlation between market power in product markets and productivity across sectors, and across firms within the same sector. On the other hand, in terms of labor market power there is a negative relationship with productivity across sectors and across firms within the same sector. Taken together, the results suggest that more productive firms and industries charge higher markups and markdowns closer to 1. One explanation could be that, when a firm is more productive, marginal costs are lower and, if they charge similar prices than their competitors, they can enjoy higher markups. At the same time, this higher product market power allows them pay a fair share to their workforce and, thus, wages are closer to the marginal product of labor.

5.3 Resource misallocation

In this section we explore the relationship between market power and total factor productivity (TFP) running a counterfactual in which we eliminate market power dispersion. Particularly, there are important hypotheses in the misallocation literature that suggest that revenue dispersion works as a sufficient statistic to the functioning of input markets. Therefore, one potential source of resource misallocation is variable market power.

Firms with higher market power than the mean within the same sector produce less than the socially efficient output, while firms with lower market power produce more than the social optimum. In this sense, the measure that matters for the functioning of markets corresponds to the dispersion in market power rather than its level and this variation can come from two sources: markups or markdowns. Therefore, our goal consists to measure the relative gains on total factor productivity of eliminating market power dispersion in product markets vs labor markets.

To that end, based on the literature pioneered by Banerjee and Duflo (2005) and Hsieh and Klenow (2009) (HK), we estimate the implications of variable market power on total factor

productivity using the model developed by HK. Although the analysis is similar in nature to their paper, in the sense that variable market power is a distortion, our goal does not consist to measure the increase in TFP in a world with no economic distortions as they do.³⁶ The idea, instead, consists to measure the relative (static) gains in TFP of eliminating variable markups vs eliminating variable markdowns.³⁷ In other words, the goal is to compare three different counterfactuals: 1) No market power distortion, 2) No markup distortion; and 3) No mark-down 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. In the case in which markups are constant across firms and in the absence of other economic distortions, the marginal revenue product of labor, MRPL, and capital, MRPK, should be equalized across firms.³⁸ This implies that “revenue productivity” defined as price times total factor productivity should not vary across firms within the same industry. However, in the presence of economic distortions, such as variable market power, MRPL or MRPK may differ across firms, diminishing TFP. For instance, [Hsieh and Klenow \(2009\)](#) provide an expression for TFP at the sector level considering economic distortions. We rewrite this expression in the case of variable market power in product and input markets.³⁹ Then, TFP in sector s can be expressed as follows:

$$TFP_s \equiv \left[\sum_{i=1}^{M_s} \left(A_{si} \cdot \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \quad (14)$$

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 , σ is the elasticity of substitution across varieties within the same sector, and $TFPR_{si} \equiv P_{si} \cdot A_{si}$ is a parameter that captures revenue productivity and, at the social optimum, is equal for all firms within the same industry. In our framework of variable markups and markdowns, we can express total revenue productivity at the firm level using the following equation:

$$TFPR_{si} \propto \frac{MU_{si}}{MD_{si}^{\theta_{L,s}}} \quad (15)$$

This means that, taking into account the effect of markups and markdowns on the average

³⁶The 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.

³⁷By static we mean holding entry, technology, and innovation constant.

³⁸This is an implication from the FOC of the firm optimization problem and factor price equalization.

³⁹In appendix D we derive all the expressions using the model developed by HK.

of TFP_s, we can rewrite equation (14) as:

$$\text{TFP}_s = \frac{\left[\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left(\frac{MD_{si}^{\theta_{L,s}}}{MU_{si}} \right)^{\sigma-1} \right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left(\frac{MD_{si}^{\theta_{L,s}}}{MU_{si}} \right)^{\sigma} \right]} \quad (16)$$

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. Then, we can express total factor productivity as:

$$\log \text{TFP}_s = \kappa - \frac{\sigma}{2} \text{Var} \left(\frac{MD_{si}^{\theta_{L,s}}}{MU_{si}} \right) \quad (17)$$

Thus, in the presence of variable market power, TFP is diminished due to resource misallocation. From equation (17), it is easy to see that if there is more dispersion on market power, the effect of resource misallocation on TFP is higher. Our goal is to estimate the relative gains of reducing market power dispersion in product vs labor markets. 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 is related to different studies that have assessed implications of different distortions on resource misallocation in the Colombian context. For example, [Eslava et al. \(2010\)](#) find that completely eliminating capital and labor adjustment frictions would yield a substantial increase in aggregate productivity in Colombia for the period 1982-1998. The increase in productivity results because allowing plants to adjust labor and capital more easily increases the market share of more efficient plants and reduces the share of less efficient plants. Our paper contributes to this literature by considering another measure that reflects resource misallocation, the dispersion in market power.

Table 12 shows our main results. 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.⁴⁰ If we eliminate all variable market

⁴⁰This 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, on average TFP increases in 19.71% across sectors, the maximum increase is 49.3%, and the minimum is 6.8%.

Likewise, the second row reports the results when we eliminate the dispersion in 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 power in product vs labor markets. Finally, in the third row we run the counterfactual of eliminating variable market power in labor markets. On average, there is an increase in TFP of 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 distortion in the economy, in particular, aggregate TFP increases by 7%.

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

6 Final Remarks

In this paper, we propose a simple methodology to disentangle firms' market power in product and labor markets based on the methodology developed by [DeLoecker and Warzynski \(2012\)](#), a labor supply choice model, and plant level production data from Colombia. First, we obtain combined measures of market power at the plant level using the production function ACF method. Then separate this measure in its two components, markups and markdowns, by estimating labor supply elasticities to the individual firm instrumenting wages with the use of intermediate inputs. This allows us to 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 low-skilled workers. For the last two results, we provide additional evidence for the mechanisms that could be at play. For example, the higher labor supply elasticity for low-skilled workers could be rationalized by the presence of a minimum wage that binds relatively more 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 a theory pioneered by Manning (2010) on firm sorting, labor market power, and spatial economics.

In terms of resource misallocation, we also measure the relative gains of eliminating market power dispersion using the model developed by HK. We find that eliminating markup dispersion has more important implications on TFP than reducing markdown dispersion. Similarly, the economic distortion of market power dispersion is attenuated in 7% due to the negative correlation between market power in product vs labor markets.

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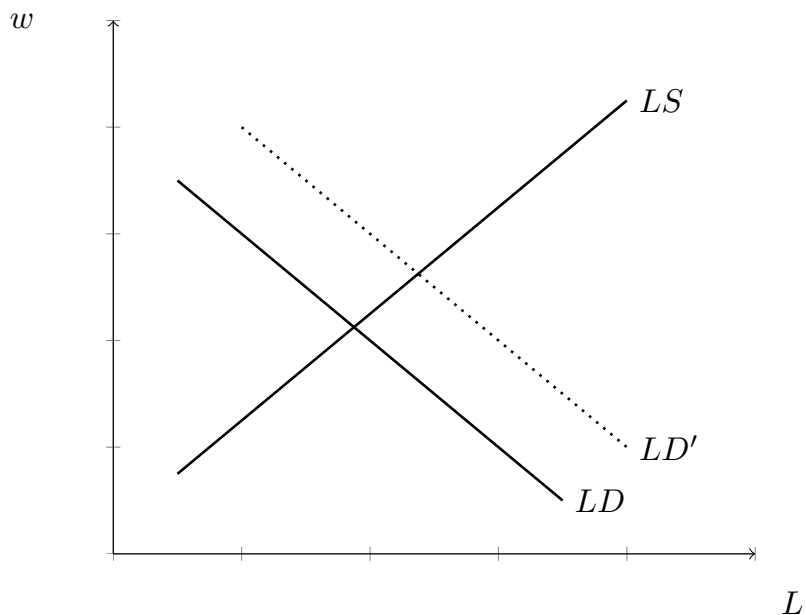
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A Figures

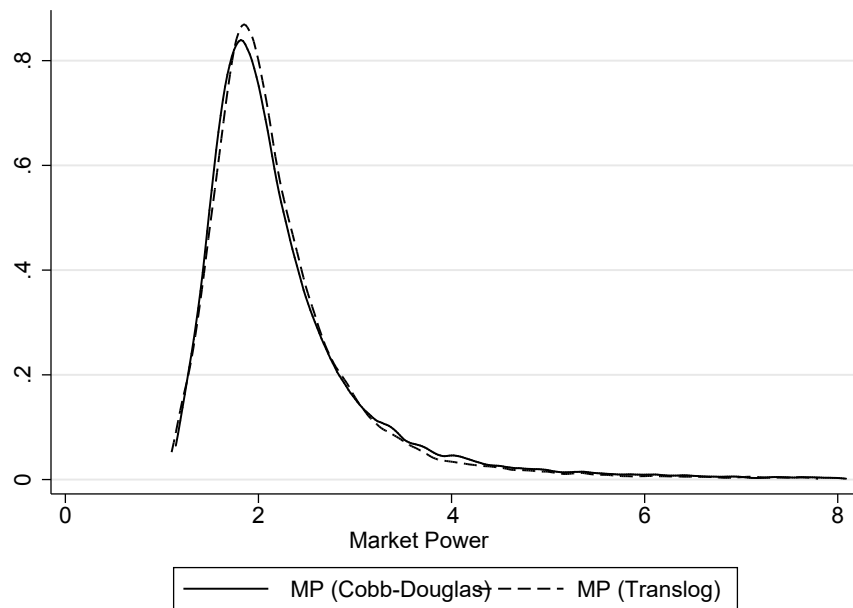
Figure 1: Identification of the labor supply to the firm

TFP shocks \longrightarrow \uparrow intermediate inputs \longrightarrow \uparrow labor demand



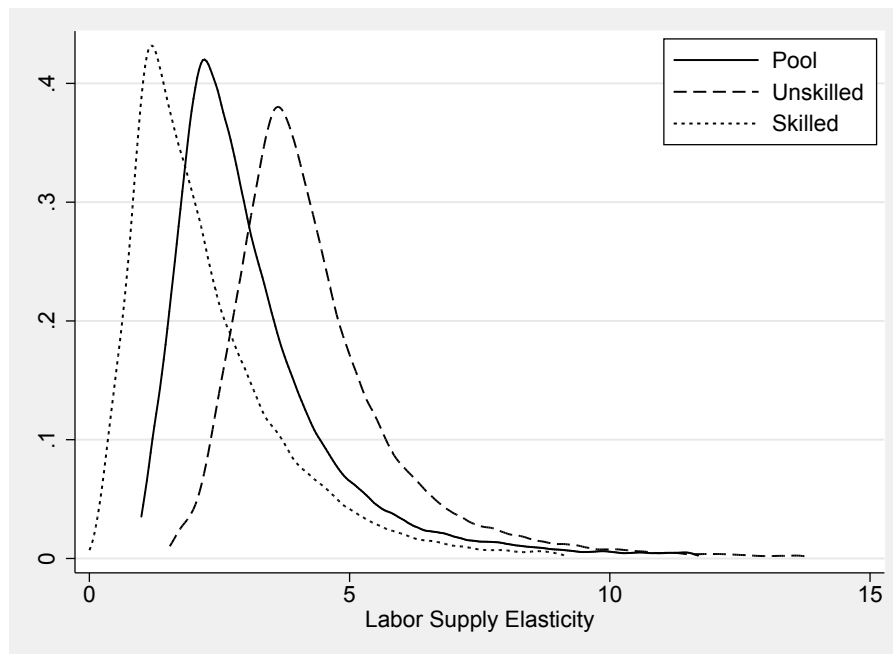
Note: this figure illustrates the spirit of our identification strategy to estimate the slope of the labor supply to the individual firm. Namely, the firm receives a productivity shock that leads to an increase in the consumption of intermediate inputs, which in turn increases the demand for workers.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

Figure 2: Distribution of market power



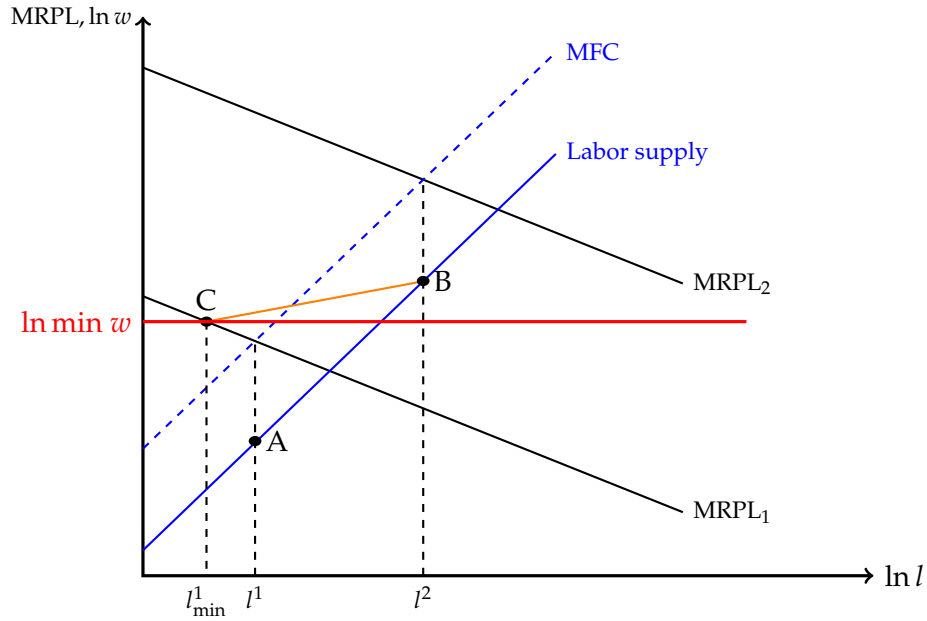
Note: this figure shows the distribution of market power across firms for both production functions: Cobb-Douglas and Translog.

Figure 3: Distribution of labor supply elasticity to the individual firm



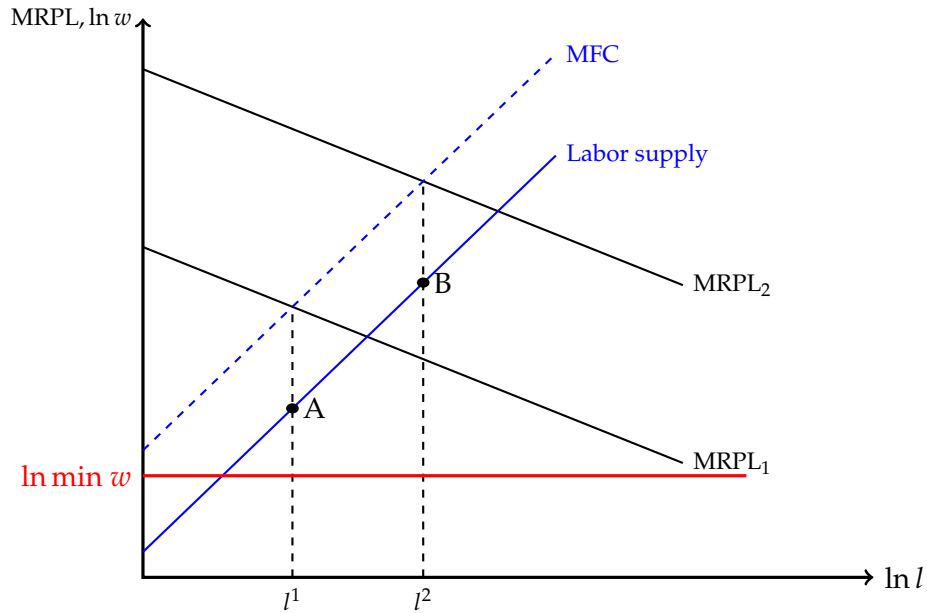
Note: This figure shows the distribution of labor supply elasticities across firms for the pool of workers, skilled and unskilled workers. The median elasticity is 2.74 for pooled workers, 1.86 for skilled workers, and 4.00 for unskilled workers.

Figure 4: Binding Minimum Wage



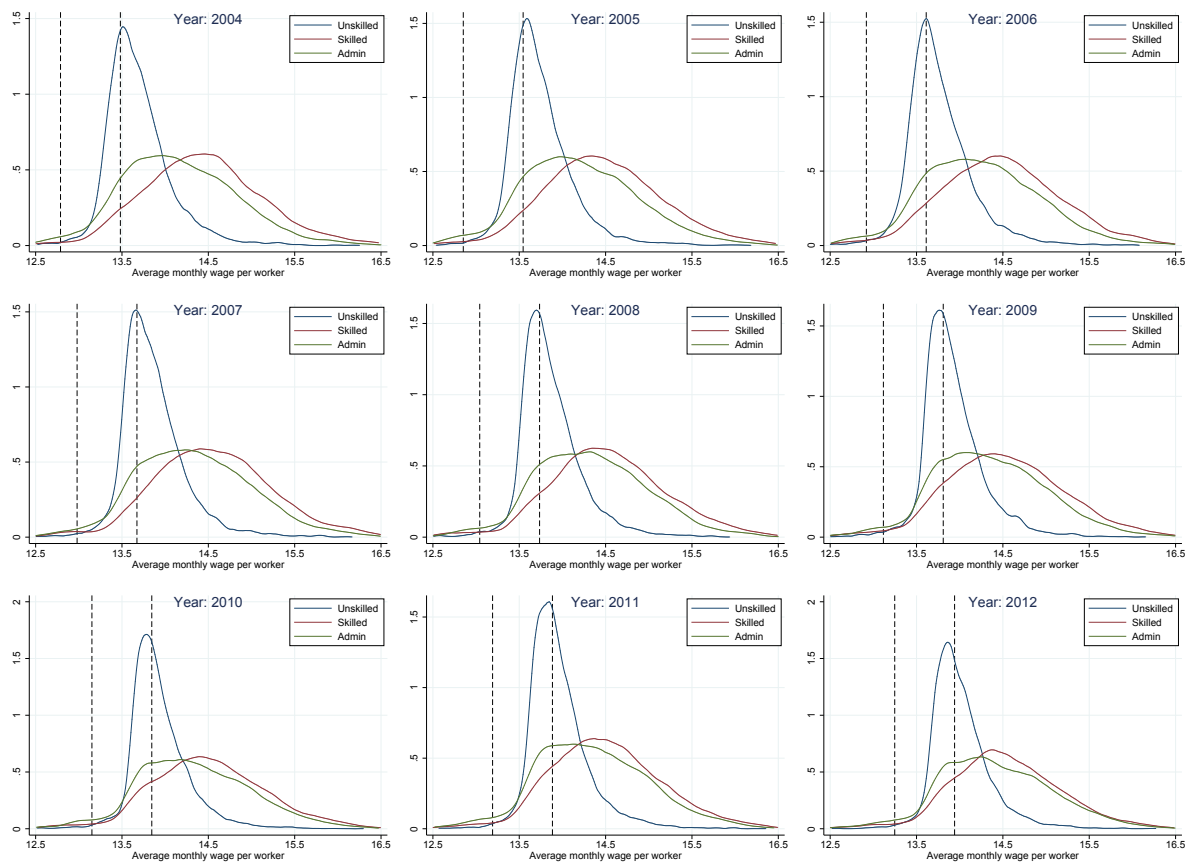
Note: This figure shows the dynamics of our identification strategy in the presence of minimum wage. In this case the minimum wage is binding, therefore the labor supply elasticity that we estimate corresponds to the slope of the orange line using equilibrium points B and C. Thus, the labor supply that is estimated is more elastic.

Figure 5: Non Binding Minimum Wage



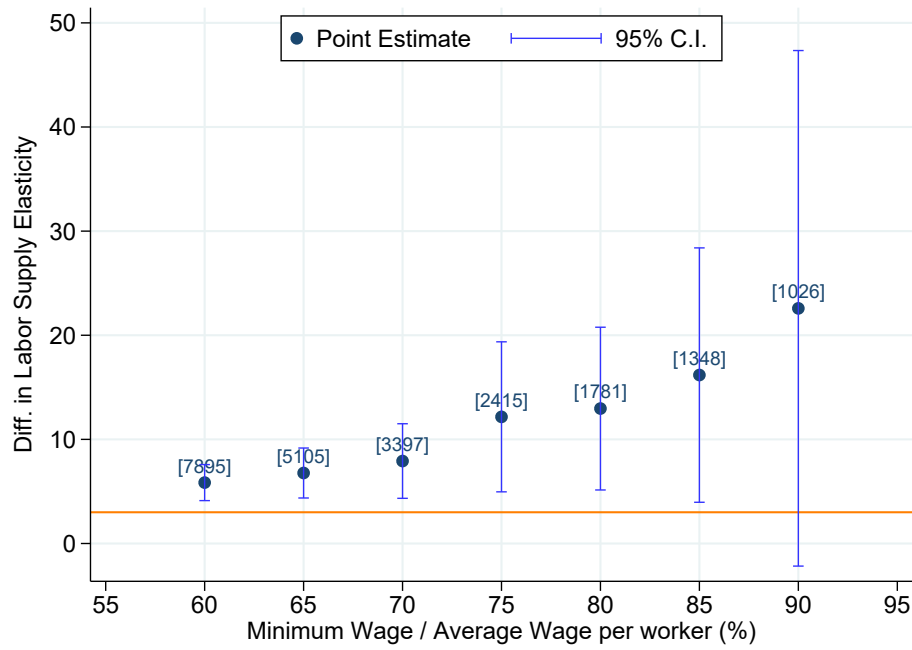
Note: This figure shows the dynamics of our identification strategy in the presence of minimum wage. In this case the minimum wage is not binding, therefore the labor supply elasticity that we estimate corresponds to the slope of the blue line.

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



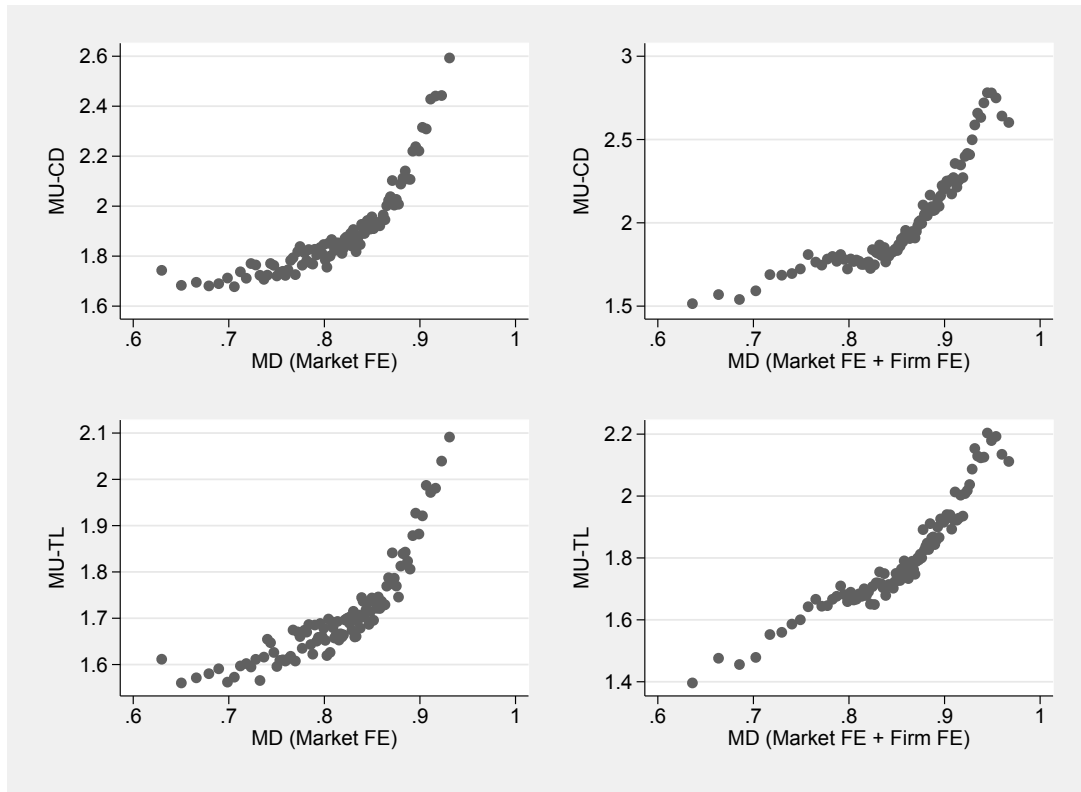
Note: this figure plots the distribution of average monthly (log) wage per worker reported by plants in the EAM survey over the period 2004-2012. Each panel shows the year-specific distribution of low-skilled production workers, high-skilled production workers, and administrative non-production workers.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

Figure 7: Labor supply elasticity and minimum wage



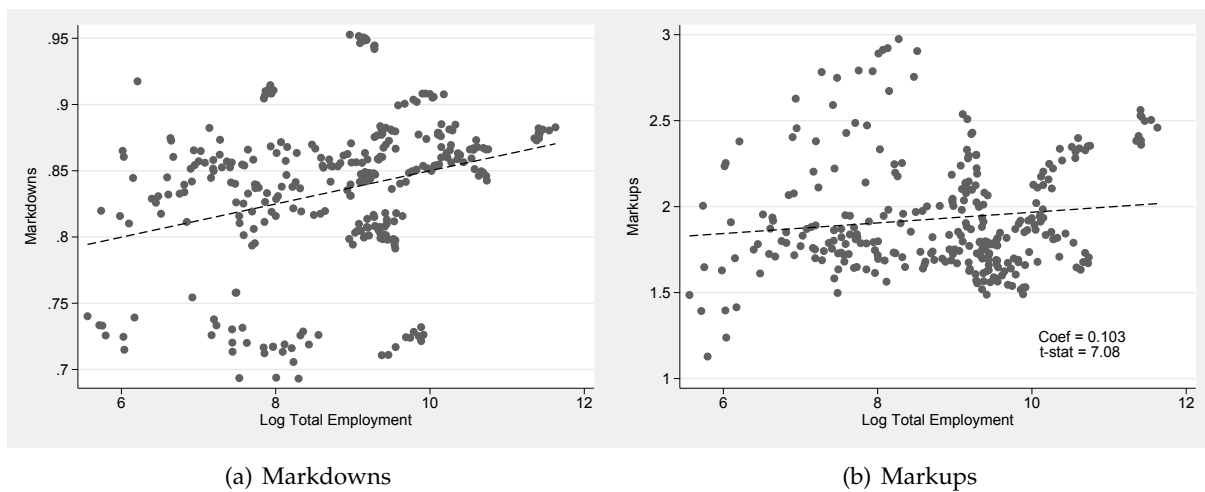
Note: This figure plots the estimated coefficient β_2 from equation (12) for different values of the ratio between the minimum wage and the average wage per worker. The coefficient captures the difference in the elasticity of labor supply between firms affected (with a ratio above the threshold) and not affected by the minimum wage (with a ratio below 60%). The horizontal orange line denotes the labor supply elasticity for the firms not affected by the minimum wage, i.e. the coefficient β_1 from equation (12). The number of plant-year observations above each threshold is presented between brackets above each dot. The figure shows that as firms get closer to a binding minimum wage, the labor supply becomes more elastic (compared to firms with a ratio below 60%).

Figure 8: Correlation of Markups and Markdowns



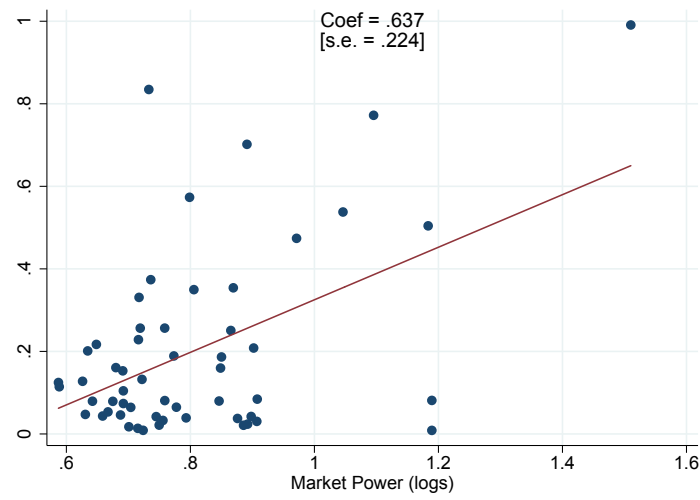
Note: this figure shows the correlation between markups and markdowns. MU-CD stands for markups estimated using the output elasticity of labor from the Cobb-Douglas specification. MU-TL stands for markups estimated using the output elasticity of labor from the Translog specification.

Figure 9: Market Power and Market Size

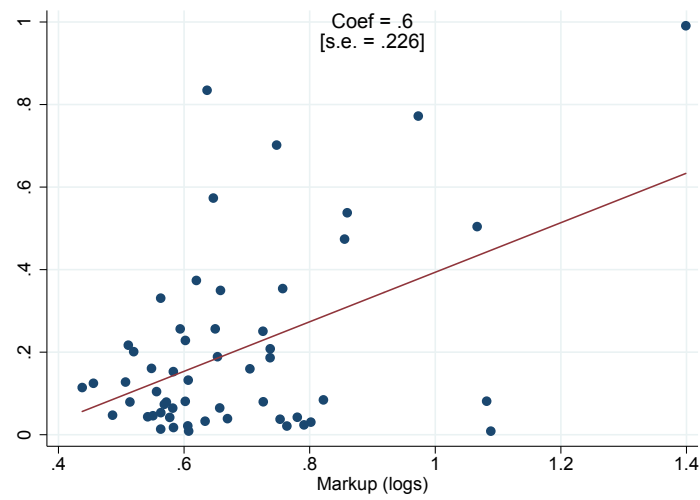


Note: this figure relates the measures of market power with labor market size computed as...

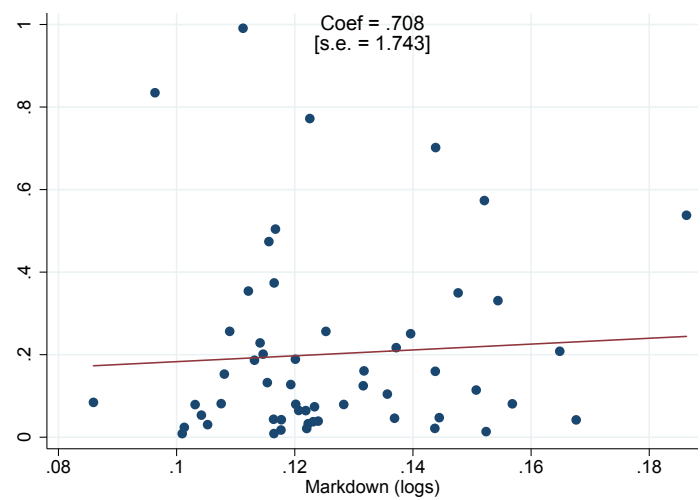
Figure 10: Market Power and Market Concentration



(a) Market Power



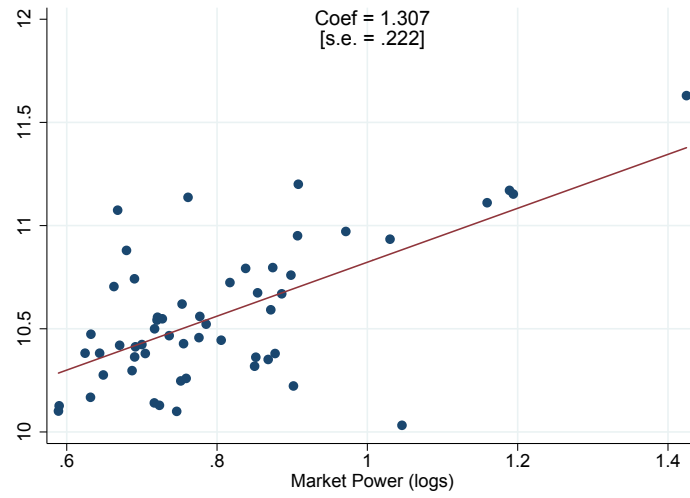
(b) Markups



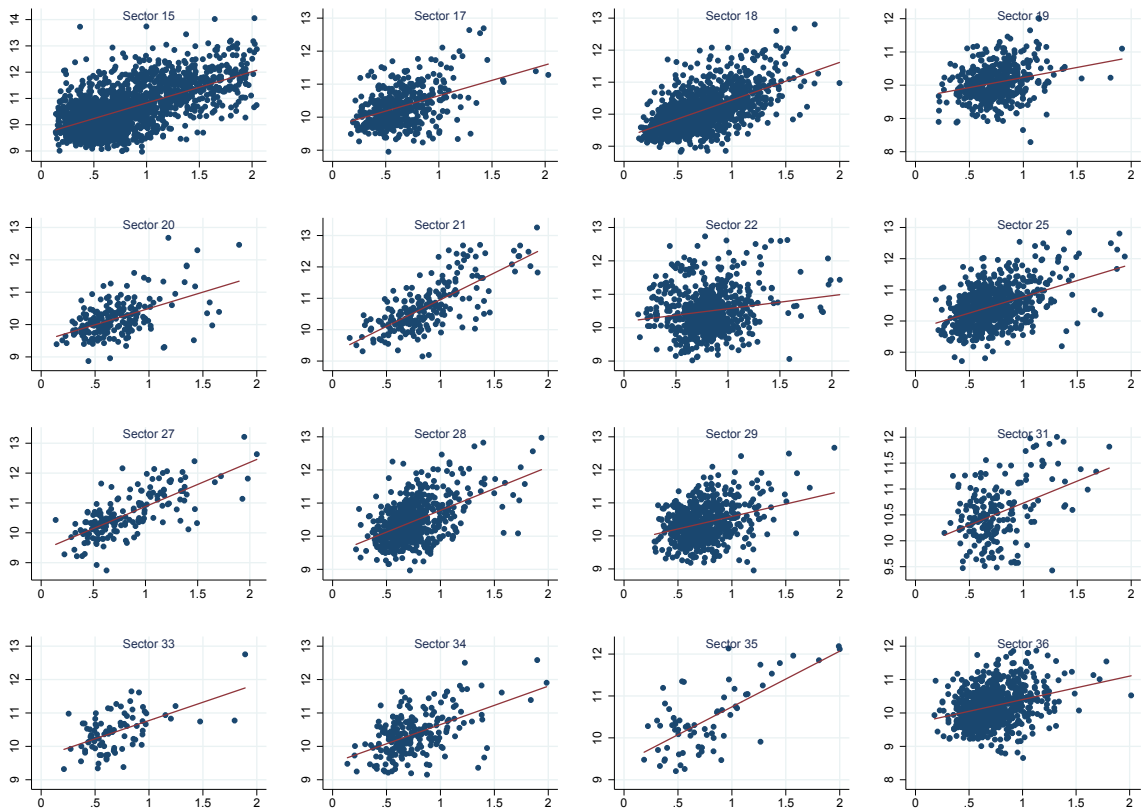
(c) Markdowns

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.

Figure 11: Productivity and Market Power



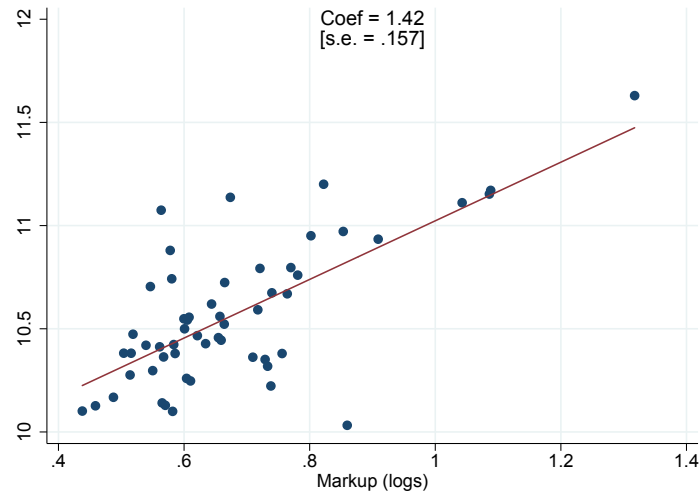
(a) Across industries



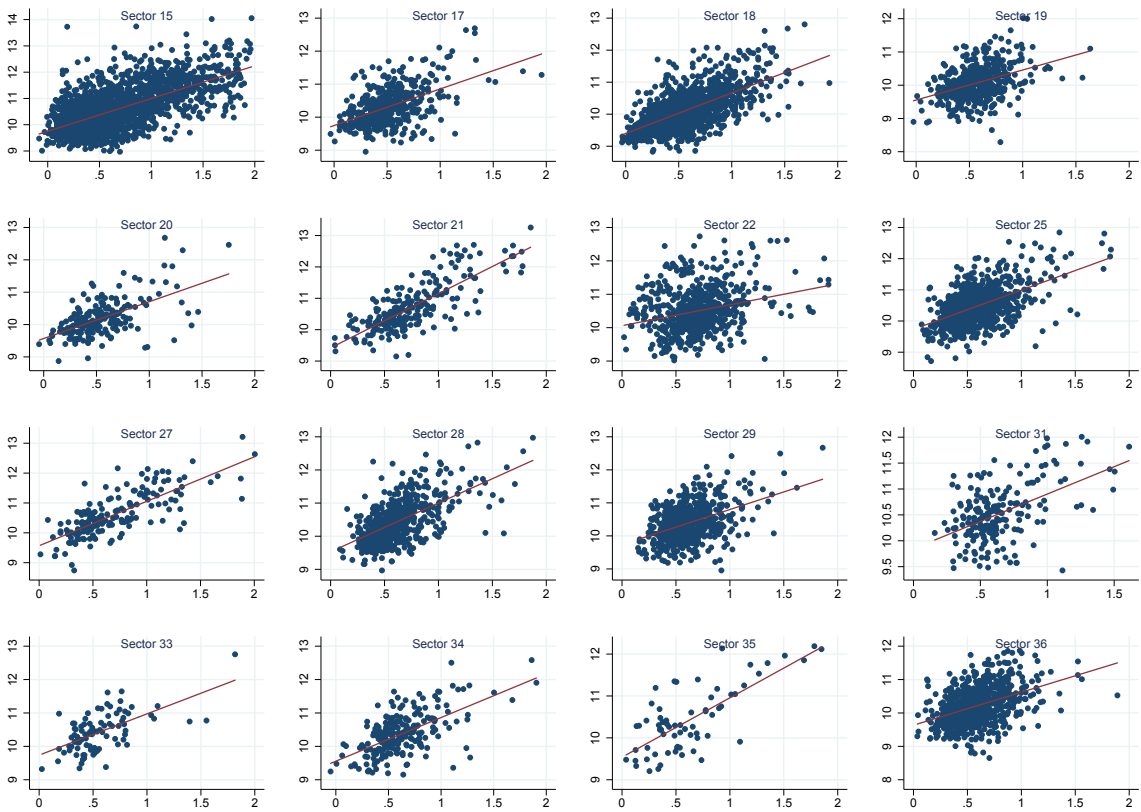
(b) Within industries

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



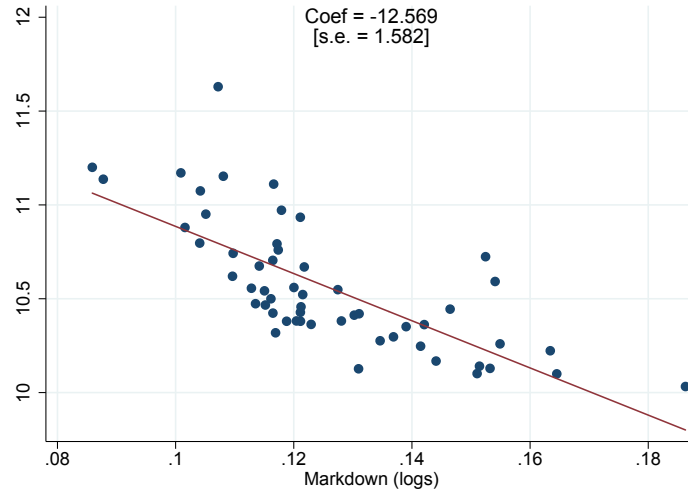
(a) Across industries



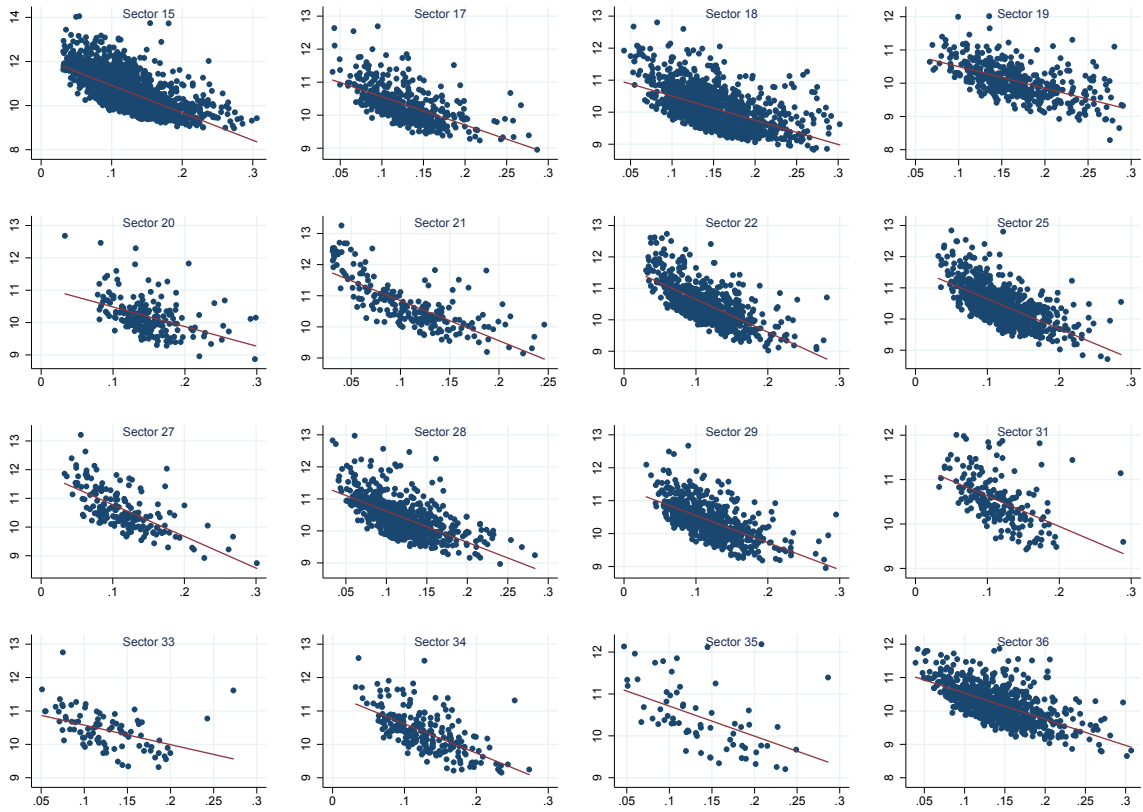
(b) Within industries

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



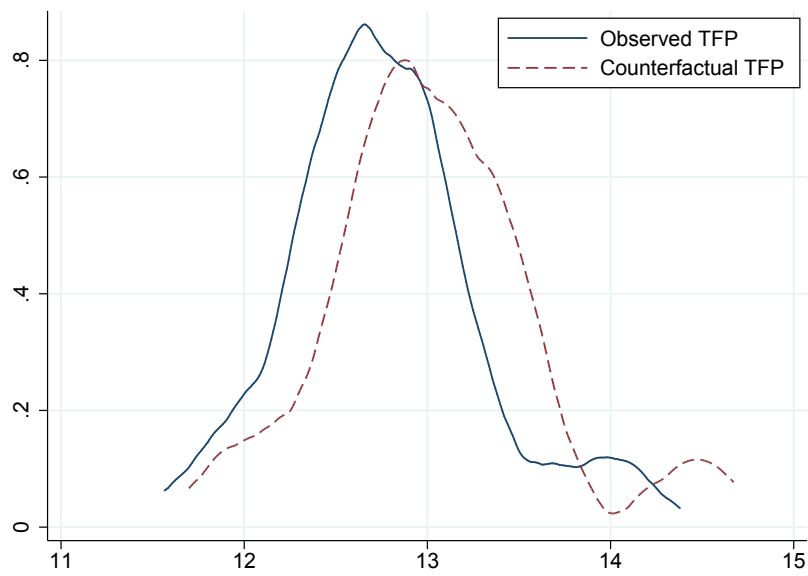
(a) Across industries



(b) Within industries

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.

Figure 14: Distribution of total factor productivity (TFP) under variable and constant 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 (16). 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.

B Tables

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	10th Perc.	50th Perc.	90th Perc	N
Labor force	74.74	135.58	8	27	178	80329
Skilled	26.39	51.29	2	8	66	80329
Unskilled	46.59	87.73	4	16	43	80329
Share Skilled	37.09%	0.22	11.76%	33.33%	68.00%	80329
Wage per worker	16.73	9.89	8.53	14.01	27.45	80329
Wage per skilled worker	23.24	19.36	7.48	18.39	44.52	80329
Wage per unskilled worker	13.44	11.06	8.14	11.77	19.35	80329
Materials (Share in total Revenue)	55.07%	0.19	29.78%	54.96%	81.33%	80329
Electricity (Share in total Revenue)	2.18%	0.032	0.60%	1.22%	4.91%	80329
Capital (Share in total Revenue)	42.41%	3.53	4.60%	21.61%	78.53%	80329
Revenue (millions pesos)	13106.33	37436.79	299.91	1728.34	28888.42	80329
VA per worker (millions pesos)	52.14	136.64	9.56	27.99	97.27	80329
Single product	32.87%	0.47	0	0	1	80329
Number of products	3.56	3.53	1.00	2.00	8.00	80329
Importer	0.18	0.39	0.00	0.00	1.00	80329
Exporter	0.24	0.43	0.00	0.00	1.00	80329

Note: Summary statistics of our main variables using the final sample of EAM. The data span the period 2002 to 2012. Nominal variables are expressed in million of Colombian pesos from 2008.

Table 2: Summary Statistics by Industry

	ISIC (1)	N (2)	(%) (3)	Labor share (4)	Wagebill /VA (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
Coke and refined petroleum products	23	452	0.56%	0.42%	0.296
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: Summary statistics by 2-digit industry.

Table 3: Production Function Estimation

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

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

	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.

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***				
Wage	0.0645	0.038	0.0555***	-0.0128***	0.2007***	0.5563***
F statistic-FS	20592	1820.44	0.000	0.000	0.001	0.006
N	77989	77989	77989	77989	77989	77989
	Panel B: Instrument Electricity (log)					
Electricity (log)	2.4255***	0.3813***				
Wage	0.0599	0.0512	-	-	0.2248***	0.5746***
F statistic-FS	1626.64	57.76	-	-	0.0057	0.0789
N	79503	79503	-	-	79503	79503
	Panel C: Number of Inputs (log)					
Number of inputs	1.7970***	0.0978				
Wage	0.1197	0.0952	-	-	0.2569***	12.312
F statistic-FS	225.368	1.05504	-	-	0.0148	12.070
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.

Table 7: Labor Supply: Skilled Workers

Dep variable	First Stage		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
	Wage		Labor Market Share		Labor Market Share	
	<i>Panel A: Instrument Materials (log)</i>					
Materials (log)	4.1706***	0.7799***				
	0.1093	0.0998				
Wage			0.0248***	0.0094***	0.1025***	0.1827***
			0.0016	0.0009	0.0023	0.0236
F statistic-FS	1459.76	61.07				
N	76785	76785	76785	76785	76785	76785
	<i>Panel B: Instrument Electricity (log)</i>					
Electricity (log)	4.8250***	0.7022***				
	0.0979	0.1657				
Wage			-	-	0.1054***	0.2492***
			-	-	0.0023	0.0607
F statistic-FS	2429.01	17.96				
N	78239	78239	-	-	78239	78239
	<i>Panel C: Number of Inputs (log)</i>					
Number of inputs	3.1152***	0.0726				
	0.2113	0.2373				
Wage			-	-	0.1719***	18.578
			-	-	0.0102	61.000
F statistic-FS	217.36	0.093				
N	76796	76796	-	-	76796	76796
Market fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	Yes	No	Yes

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.

Table 8: Labor Supply: Unskilled Workers

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)	1.3617***	0.2820***				
	0.0516	0.0458				
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	75963	75963
	Panel B: Instrument Electricity (log)					
Electricity (log)	1.4687***	0.2918***				
	0.0572	0.0881				
Wage			-	-	0.3794***	0.8388***
			-	-	0.0153	0.2552
F statistic-FS	659.28	10.97				
N	77158	77158	-	-	77158	77158
	Panel C: Number of Inputs (log)					
Number of inputs	0.8709***	0.3142**				
	0.0905	0.1355				
Wage			-	-	0.4947***	0.3614***
			-	-	0.0481	0.1623
F statistic-FS	92.61	5.38				
N	75972	75972	-	-	75972	75972
Market fixed effects	Yes	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.

Table 9: Labor Supply Elasticity by Industry

	<u>Pool of workers</u>		<u>Unskilled workers</u>		<u>Skilled workers</u>	
	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
Coke and refined petroleum	3.52	9.80	4.31	9.97	2.13	3.80
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.

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

	(1)	(2)	(3)	(4)	(5)
	<i>MP</i>	<i>MU</i>	<i>MD</i>	<i>MD-Unskilled</i>	<i>MD-Skilled</i>
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).

Table 11: Market Power and Firm Characteristics

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

Note: dependent variable is the log of market power. 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.

Table 12: Counterfactuals *ala* Hsieh and Klenow

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

C Output Elasticity Estimation

In this section we explain the method developed by ACF and used by DLW 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 a standard GMM model to identify the production function coefficients. Let's consider a value added Translog production function:

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

where l is the log of labor, in this case the variable input, and k is the log of capital. In the case of the Cobb Douglas production function $\beta_{ll} = \beta_{kk} = \beta_{lk} = 0$.⁴¹ In a first stage, ACF fit the following model

$$y_{it} = \phi(l_{it}, k_{it}, m_{it}, \mathbf{z}_{it}) + \epsilon_{it}$$

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

$$\phi_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + h_t(m_{it}, k_{it}, \mathbf{z}_{it})$$

where m is the log of intermediate materials and energy.⁴² The second stage relies on the law of motion for productivity providing estimates for all coefficients of the production function,

$$\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}$$

$$\omega_{it} = \gamma_{1t} \omega_{it-1} + \gamma_{2t} \omega_{it-1}^2 + \gamma_{3t} \omega_{it-1}^3 + \xi_{it}$$

After the first stage, ACF are able to compute a level of productivity ω_{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 β , $\xi_{it}(\beta)$,

⁴¹We also include in the production function estimation time fixed effects and 2 digit ISIC industry fixed effects.

⁴²We include interaction of these variables and year dummy variables.

and form moments to obtain estimates of the production function,

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

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:

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

$$\hat{\theta}_{it}^{L_{tl}} = \hat{\beta}_l + 2\hat{\beta}_{ll}l_{it} + \hat{\beta}_{lk}k_{it}$$

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 ϵ_{it} from the first stage to compute the corrected expenditure share for input X_{it} as follows

$$\hat{\alpha}_{it} = \frac{P_{it}^X X_{it}}{P_{it} \frac{\tilde{Q}_{it}}{\exp(\hat{\epsilon}_{it})}}$$

With all these ingredients it is possible to estimate market power for plant i at time t .

D Hsieh and Klenow model

In this section we describe the model developed by [Hsieh and Klenow \(2009\)](#) and rewrite their main equations in terms of variable markups and variable markdowns. Moreover, we derive an expression of total factor productivity in terms 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:

$$Y_s = \sum_{i=1}^{M_s} \left(Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad (19)$$

Where Y_{si} is a differentiated product and σ is the elasticity of substitution across varieties within sector s . By the properties of CES, the price index in sector s is:

$$P_s = \sum_{i=1}^{M_s} \left(P_{si}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \quad (20)$$

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.

$$Y_{si} = A_{si} K_{si}^{1-\theta_{Ls}} L_{si}^{\theta_{Ls}} \quad (21)$$

Where θ_{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:

$$MRPL_{si} \equiv \theta_{Ls} \cdot A_{si} \cdot \left(\frac{P_{si} Y_{si}}{L_{si}} \right) = w \cdot \left(\frac{MU_{si}}{MD_{si}} \right) \quad (22)$$

$$MRPK_{si} \equiv (1 - \theta_{Ls}) A_{si} \cdot \left(\frac{P_{si} Y_{si}}{K_{si}} \right) = R \cdot MU_{si} \quad (23)$$

$$P_{si} = \frac{1}{A_{si}} \left(\frac{R}{1 - \theta_{Ls}} \right)^{1-\theta_{Ls}} \left(\frac{w}{\theta_{Ls}} \right)^{\theta_{Ls}} \frac{MU_{si}}{MD_{si}^{\theta_{Ls}}} \quad (24)$$

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 s as:

$$\frac{1}{MR\bar{P}L_s} \equiv \sum_{i=1}^{M_s} \frac{1}{MRPL_{si}} \frac{P_{si}Y_{si}}{P_sY_s} \quad (25)$$

$$= P_s^{\sigma-1} \sum_{i=1}^{M_s} \frac{1}{MRPL_{si}} \left(A_{si} \cdot \frac{MU_{si}}{MD_{si}} \right)^{\sigma-1} \quad (26)$$

$$\frac{1}{MR\bar{P}K_s} \equiv \sum_{i=1}^{M_s} \frac{1}{MRPK_{si}} \frac{P_{si}Y_{si}}{P_sY_s} \quad (27)$$

$$= P_s^{\sigma-1} \sum_{i=1}^{M_s} \frac{1}{MRPK_{si}} \left(A_{si} \cdot \frac{MU_{si}}{MD_{si}} \right)^{\sigma-1} \quad (28)$$

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

$$TFP_s = \left(\frac{P_sY_s}{L_s} \right)^{\theta_{Ls}} \left(\frac{P_sY_s}{K_s} \right)^{1-\theta_{Ls}} \frac{1}{P_s} \quad (29)$$

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

$$L_s = \sum_i^{M_s} \left(\frac{\theta_{Ls} \cdot P_{si}Y_{si}}{MRPL_{si}} \right) \quad (30)$$

$$= P_sY_s\theta_{Ls} \sum_i^{M_s} \left(\frac{1}{MRPL_{si}} \frac{P_{si}Y_{si}}{P_sY_s} \right) \quad (31)$$

$$= \theta_{Ls} \frac{P_sY_s}{MR\bar{P}L_s} \quad (32)$$

Aggregating over all firms

$$K_s = \sum_i^{M_s} \left(\frac{(1-\theta_{Ls}) \cdot P_{si}Y_{si}}{MRPK_{si}} \right) \quad (33)$$

$$= P_sY_s(1-\theta_{Ls}) \sum_i^{M_s} \left(\frac{1}{MRPK_{si}} \frac{P_{si}Y_{si}}{P_sY_s} \right) \quad (34)$$

$$= (1-\theta_{Ls}) \frac{P_sY_s}{MR\bar{P}K_s} \quad (35)$$

Then TFP can be expressed as:

$$TFP_s = \left(\frac{M\bar{R}PL_s}{\theta_{L_s}} \right)^{\theta_{L_s}} \left(\frac{M\bar{R}PK_s}{1 - \theta_{L_s}} \right)^{1 - \theta_{L_s}} \frac{1}{P_s} \quad (36)$$

Finally using equations 26 and 28 we get that:

$$TFP_s = \left[P_s^{\sigma-1} \left(\frac{w}{\theta_{L_s}} \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left(\frac{MD_{si}}{MU_{si}} \right)^{\sigma} \right)^{\theta_{L_s}} \left(\frac{R}{1 - \theta_{L_s}} \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left(\frac{MD_{si}}{MU_{si}} \right)^{\sigma} \right)^{1 - \theta_{L_s}} \right]^{-1} \left(\frac{1}{P_s} \right) \quad (37)$$

Plugging in P_s from equation 20 we conclude that:

$$TFP_s = \frac{\left[\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left(\frac{MD_{si}^{\theta_{L_s}}}{MU_{si}} \right)^{\sigma-1} \right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \left(\frac{MD_{si}^{\theta_{L_s}}}{MU_{si}} \right)^{\sigma} \right]} \quad (38)$$

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.