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

Dario Tortarolo† Roman D. Zarate‡

UC Berkeley UC Berkeley

September 2018
First Version: August 2017

Abstract

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

*We are very grateful to David Card, Patrick Kline, and Andrés Rodríguez-Clare for all their guidance and support in this project. We also thank Irene Brambilla, Marcela Eslava, Ben Faber, Thibault Fally, Cecile Gaubert, Juliana Londoño-Vélez, Enrico Moretti, and Hernán Ruffo, as well as seminar participants at the CAF symposium and UC Berkeley Trade and Labor Lunch for very helpful feedback. We are very grateful to DANE for granting us remote access to the data making this work possible. The views expressed are those of the authors alone and do not reflect the views of DANE. Financial support from CAF Development Bank of Latin America and the Clausen Center at UC Berkeley is gratefully acknowledged.

†Department of Economics, UC Berkeley, 522 Evans Hall, Berkeley, CA. E-mail: dtortarolo@berkeley.edu

‡Department of Economics, UC Berkeley, 660 Evans Hall, Berkeley, CA. E-mail: romand@berkeley.edu

The estimation of market power has been of long interest in economics. On the one hand, industrial organization and trade economists have developed different methods to measure *markups* since they provide relevant information on different market outcomes. For example, DeLoecker and Eeckhout (2017) show that the increase in average *markups* in the last three decades in the US can account for a number of secular trends that include the decrease in the labor share. On the other hand, recent studies in labor economics have made efforts to estimate labor market power since ignoring the existence of employer market power could lead to incorrect conclusions on the driving force behind changes in wage inequality (Manning, 2003b); and a monopsony model rationalizes different facts found by the employer-employee literature. For example, the fact that wages of workers with similar skills vary across firms (Card et al., 2018).[1]

However, the question of whether labor markets and product markets are imperfectly competitive has been typically approached separately for each market. While a large body of literature estimates *markups*, empirical evidence on *markdowns* is more scant. There are two main reasons for this. First, the standard neo-classical model assumes that firms do not have market power in labor and, therefore, a worker's wage only depends on its own ability. Second, it is hard to find quasi-experimental evidence at the firm level to estimate residual labor supply elasticities.[2] This paper aims to approach this question from an integrated perspective and measure the extent of market power of firms in both product and labor markets using production-level data.

Although combined market power is the relevant metric for resource misallocation, disentangling product and labor market power matters for at least two reasons. First, it is important for policy concerned about efficiency to understand whether market power is on the product or labor side. This can indeed be an important step toward determining which frictions governments should prioritize. Second, there are different implications for inequality depending on the source of market power. For example, labor market power exacerbates wage inequality, since workers with similar characteristics get different salaries depending on which firm do they work. Therefore, the estimates of *markdowns* would be relevant for policy aimed at decreasing wage inequality. Alternatively, the estimates of *markups* would be informative for consumption inequality. This is because consumers with different preferences and product shares in their consumption basket may face different price indexes and, as a result, changes in *markups* affect individuals differently.[3]

The most standard technique in the literature to estimate *markups* from the production side

[1] We interpret "monopsony" or "oligopsony" as employers having wage-setting power.

[2] Nevertheless, interest in labor market power has grown in recent years. For example, see Kline et al. (2017), Garin and Silverio (2017), and Azar et al. (2017).

[3] A new literature in economics studies this and emphasizes the role that non-homothetic preferences play for consumption inequality. For more on this topic, the reader can look at Faber and Fally (2017) and Jaravel (2016).

is the method developed by DeLoecker and Warzynski (2012) - henceforth DW, based on the formula by Hall (1988). In this paper, we reinterpret this formula as a combined measure of market power for any variable input, including labor. We are able to separate this combined measure of market power into *markups* and *markdowns* by estimating the elasticity of labor supply to the firm directly. We also show how our methodology can be used to decompose the misallocation due to product vs. labor market power using the model from Hsieh and Klenow (2009) - henceforth HK.

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

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 cost in total output (right-hand side). 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 exert more market power when they get relatively more output out of the labor input than the cost it represents to the plant. This could be explained by firms setting prices above the marginal cost (*markup*) and/or firms setting wages below the marginal revenue product of labor (*markdown*).

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

Our next step is to separate overall market power into a *markup* and a *markdown*. To this end, we develop an empirical strategy to estimate *markdowns* using firm-level production data. We follow the Roy-type model developed by CCHK in which workers have heterogeneous preferences for different workplaces and firms compete oligopsonistically. From the model, we get a reduced-form equation for the relationship between labor and wages that we use to estimate the labor supply elasticity to the individual firm. Since this equation is endogenous by nature, we identify the coefficient of wages using intermediate inputs as an instrumental variable.

Ideally, one would like to instrument wages per efficiency units with productivity shocks at the firm level. However, since TFP shocks are not observable, we adopt an old idea from the production function literature in which materials work as a proxy for TFP shocks. Our exclusion restriction is that a positive correlation between changes in TFP and changes in the use of intermediate inputs within firms shifts the labor demand curve but not the labor supply curve to the firm.[4] 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.

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

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

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

We find a negative correlation between product and labor market power and more elastic labor supply curves for unskilled workers. For the last two results, we provide additional evidence for the mechanisms that could be at play.[5] Similarly, 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

[4] Although we believe that our strategy performs well in general, there are some potential threats to our exclusion restriction that cannot be ruled out, such as factors simultaneously affecting the use of materials and shifting the labor supply curve to the firm.

[5] For example, the higher labor supply elasticity for unskilled workers could be rationalized by the presence of a minimum wage. In the cost minimization problem one can include an additional restriction that accounts for the minimum wage that will be more binding for firms with a higher composition of unskilled workers.

of these patterns based on a theory pioneered by Manning (2010) about firm sorting, labor market power, and spatial economics. Regarding resource misallocation, we show that the relative TFP gain of reducing the dispersion of *markups* is more important than reducing the dispersion of *markdowns*. In our exercise, TFP increases approximately 20% when we remove market power dispersion; 26% when we only remove *markup* dispersion, and 2.5% when we only remove *markdown* dispersion.

The remainder of the paper is organized as follows. Section 1 provides a short summary of the related literature. In section 2, we present our empirical strategy based on DW and CCHK. 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 data for our empirical application. Section 4 reports our main results and characterizes firms and sectors according to product and labor market power. We also quantify the negative relationship between market power dispersion in both markets and aggregate TFP following HK. Finally, section 6 concludes.

1 Related Literature and Contribution

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 DW and DeLoecker et al. (2016) who estimate the relationship between prices and marginal costs using plant-level production data in an environment in which firms exert market power and are heterogeneous.

On the labor market side, this article fits into the relatively scarce literature that has attempted to measure labor market power (e.g., see Manning (2010) and Ashenfelter et al. (2010) for recent reviews; and Kline et al. (2017) and Garin and Silverio (2017) for new identification strategies). It is also related to a new literature that considers imperfect labor markets to explain the relationship between the dispersion of firms' productivity and wage inequality (Card et al., 2018), as well as labor market concentration (Azar et al., 2017) and wage stagnation in the U.S. (Naidu et al., 2018).

Our work also speaks to recent research that addresses product and labor market imperfections simultaneously based on Hall's approach. Crépon et al. (2005) and Dobbelaere and Mairesse (2013) 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. The authors also classify industries into different regimes based on the degree of market power in product and labor markets. In addition, Dobbelaere and Kiyota (2018) explore the relationship between a firm's internationalization status and the degree of market imperfection in product and labor markets.

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

Our study differentiates from previous work in meaningful ways. First, we estimate production functions using the method of Ackerberg et al. (2015) which addresses endogeneity issues derived from unobserved productivity and input choices. Second, and unlike previous studies, we estimate a labor supply Roy model using materials as an instrumental variable, which lets us identify the elasticity of labor supply to the individual firm directly. To the best of our knowledge, this is the first paper that estimates the elasticity of labor supply to the individual firm using a BLP-type approach and intermediate inputs as an instrumental variable for wages, a strategy that can be easily applied in other countries as well. Hence, by combining tools from IO and the Labor literature, we estimate two equations in an over-identified setting, which imposes more discipline to the empirical analysis relative to other papers. Lastly, we connect the literature of *markups*, *markdowns*, and resource misallocation by measuring the relative gains in TFP of eliminating variable market power in product vs labor markets.

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

2 Empirical Strategy

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

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

where X_{it}^v corresponds to the quantity of a variable input, V is the number of variable inputs, L_{it} corresponds to labor, K_{it} to capital stock, and 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 behaves as a monopoly in the market of the good that it produces, and as a monopsony in the labor market. Then, the Langragian associated to the cost minimization problem is:

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

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

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

where ϵ_{it}^{Lw} denotes the elasticity of labor supply to the firm, and therefore, the term between parentheses is the inverse of the *markdown*, MD_{it}. The interpretation of this term is as follows: if wages at firm i increase by 1%, the share of workers that are willing to work at this firm increases by ϵ_{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 we can express the marginal cost as the ratio between prices and *markups* ($\lambda_{it} = \frac{P_{it}}{MU_{it}}$), then we arrive to a combined measure of market power, MP_{it}:

$$MP_{it} \equiv \frac{MU_{it}}{MD_{it}} = \frac{\theta_{it}^L}{\alpha_{it}^L}, \tag{3}$$

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. This is the key equation that guides our empirical analysis. Note also that equation (3) can be generalized for any variable input X_{it}^v as:

$$MP_{it}^v = \frac{MU_{it}}{MD_{it}^v} = \frac{\theta_{it}^v}{\alpha_{it}^v}, \tag{4}$$

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

$$MU_{it} \equiv \frac{p_{it}}{mc_{it}} = \frac{|\epsilon^p_{it}|}{|\epsilon^p_{it}| - 1} \qquad\qquad MD_{it} \equiv \frac{w_{it}}{MRPL_{it}} = \frac{\epsilon^{Lw}_{it}}{\epsilon^{Lw}_{it} + 1}, \tag{5}$$

where ϵ^p_{it} is the product-demand elasticity and ϵ^{Lw}_{it} is the elasticity of labor supply to the firm.[6] The first equation is a rearrangement of the Lerner index, while the second equation is the counterpart for monopsonies.

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

Several recent papers have estimated firm-level *markups* by focusing on the right hand side of equation (4), implicitly assuming perfect competition in labor markets (e.g., see DeLoecker et al. (2016)).[7] In that special case, workers are paid their marginal product of labor and *markdowns* are equal to one. When labor markets are not competitive, however, the right hand side of equation (4) identifies market power in both product and labor markets.

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

2.1 Production function estimation

The estimation and identification of θ^v_{it} has received a lot of attention in the IO literature. One way of getting consistent output elasticities is to estimate production functions using "proxy methods" developed by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg

[6] Based on this equation, the more inelastic the labor supply curve to the employer, the wider the gap between the marginal product of labor and the wage. This gap is also known as the "rate of exploitation" (Hicks, 1932).

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

et al. (2015).[8] This method is also used by DeLoecker and Warzynski (2012) who estimate *markups* at the firm level. We adopt the same approach as Ackerberg et al. (2015) (ACF, hereafter) to estimate the output elasticity with respect to labor which is the key parameter that allows to pin down our combined measure of market power.

Since the approach we adopt is a standard technique to estimate production functions, we refer the reader to Appendix C for more details on the 2-step method to estimate the output elasticity of variable inputs. In practice, the implementation of this method requires parametric assumptions on the functional form of the production function (equation 12). We follow DeLoecker and Warzynski (2012) and consider a Cobb-Douglas and a Translog specification:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{6}$$

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

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

To decompose aggregate market power into *markups* and *markdowns* we adopt a discrete choice method of the IO literature based on Berry (1994) and Berry et al. (1995) -henceforth BLP- that allows to pin down price-demand elasticities or labor-supply elasticities. However, since it is easier to define a labor market than a product market, our identification hinges on the estimation of residual labor supply elasticities. We define a labor market as region-sector-year cell. We based our theoretical framework on the model developed by CCHK, which is similar to Roy models that assume idiosyncratic logistic shocks. In the next section we explain our empirical strategy to estimate labor supply elasticities in more detail.[9]

[8] OLS estimates are typically biased since observed inputs are chosen as a function of unobserved determinants of production. The idea of the "proxy methods" is to assume that an input (e.g., material) is a strictly increasing function of a scalar, firm-level, unobserved productivity shock (conditional on capital stock). One can then invert this input demand function, and thus control for the unobserved productivity shock by conditioning on a nonparametric representation of that inverse function (i.e., a nonparametric function of capital stock and materials).

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

2.2 Labor supply elasticity

We pin down *markdowns* by estimating labor supply elasticities to the individual firm.[10] 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 at firm i is given by:

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

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

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

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

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

where $\gamma_{m(i,t)}$ is a market fixed effect defined as a region-industry-year cell. Note that we get rid off the denominator in (9) by including market fixed effects. A simple OLS regression of equation (10) leads to a biased 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 widely used as a proxy for productivity (Levinsohn and Petrin, 2003) and, second, our exclusion restriction implies that after controlling for firm fixed effects, a higher usage of materials does not shift the labor supply curve, an assumption we believe to be plausible in practice.[11] Finally, the elasticity of the labor supply

[10] Note that this elasticity is different from the macro labor supply elasticity based on labor market models in which workers decide between leisure, consumption, and hours of work.

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

to the individual firm implied by the model is:

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

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 using the empirical methodology from BLP. However, we believe that our preliminary results are consistent with the Bargaining literature in labor markets. Finally, note that equation (10) can be estimated separately for different types of workers (e.g., by skill groups). In the empirical section, we explore the heterogeneity by high-skilled and low-skilled workers.

3 Data

The empirical analysis relies on plant-level production data from Colombia's Annual Manufacturing Survey (EAM) collected by DANE, the Colombian statistical agency. The EAM is a uniquely rich census of manufacturing plants with 10 or more employees. It provides standard plant survey information plus much more rare data on physical quantities and unit values of manufactured products and used inputs.[12] We observe approximately 5,000-7,000 plants in each year, producing in and purchasing from approximately 4,000 distinct eight-digit product codes (comparable to the 6-digit codes of the Harmonized System).

In the analysis we narrow the attention to the period 2002-2012. The definition of the variables used in the analysis follows closely a series of papers that have used the EAM census in the past (e.g., Eslava et al. (2013)). Employment includes both paid and unpaid production and administrative workers. Labor costs include wages, salaries, bonuses and any supplemental labor costs. To consider differences in quality or productivity, labor is computed in efficiency units, where physical units are normalized by the ratio between the plant average wage and the average industry wage. We use perpetual inventory methods to construct plants' stock of capital. Intermediate inputs include materials, electricity, fuels, and other expenditures. All variables are deflated using industry-level deflators.[13]

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

[12]The more standard variables are: sales, value added, input use, investment, employment and wage bill of professional production workers, non-professional production workers, and administrative workers; and broader information such as ownership structure, foreign capital participation, year in which activities began, geographic location, and industry affiliation at the four-digit level of the ISIC Revision 3.

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

have missing values on the key variables;[14] we drop any plant-year observation for which a key variable differed by more than a factor of 6 with respect to the median of the plant in the whole period of analysis; we winsorize the key variables within each year to the values of percentile 1 and 99.[15]

Table 1 reports basic summary statistics. The final sample includes 80,329 plant-year observations. Plants employ an average of 75 workers and there is large variation across plants-years. The share of skilled workers is on average 37 percent and the share of unskilled workers is 63 percent. On average, the wage per worker is twice as large for skilled than unskilled workers.[16] 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. They account about 50 percent of employment in manufacturing and observations in the sample (Columns 3 and 4 of Table 2). The average share of labor costs on value added is 0.471 (this is 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 suggests that we need to allow for differences in production function parameters as part of the procedure to estimate our measure of market power. Therefore, in our analysis we report results estimating heterogeneous coefficients by industry.

4 Results

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

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

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

[16]Skilled 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. 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.[17] The last row of each panel reports the average returns to scale which are slightly higher than 1.[18]

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

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

[17] Note that the number of observations is lower in the ACF method. This is because the 2-step GMM uses the lag of labor as an instrument and therefore we lose the observations from the base year.

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

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 elasticities

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

Table 6 shows the results when we use total number of workers hired by each firm as our dependent variable. The first stage of the IV estimation suggests that there is a strong, positive, and similar-in-magnitude correlation between wage per worker and materials (panel A) and electricity (panel B), but it is weaker in the case of the number of inputs (panel C).[19]. In the second stage, we use the variation from 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 statistically significant effect. Reassuringly, the three specifications provide very similar coefficients. If we also add firm fixed effects to control for unobserved heterogeneity, then the coefficients become larger but are still similar in magnitude.[20]

In Tables 7 and 8 we explore the heterogeneity of labor supply by separating the analysis into skilled and unskilled workers.[21] 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

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

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

[21] We define unskilled workers as production workers without a professional degree, and skilled workers as the sum of production workers with a professional degree and administrative workers.

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 a productivity shock. Hence, since the three instruments provide very similar results, in the rest of the paper we focus the attention to the labor supply estimates that use materials as an instrumental variable.[22]

Finally, we translate these estimates into labor supply elasticities to the individual firm using equation (11). Table 9 reports some summary statistics and Figure 3 presents the distribution of labor supply elasticities across plants. For the pool of workers, we find median elasticities of 2.74 and 7.62 for specifications with market FE and firm FE, respectively, with relatively little variation across sectors. However, There is more variation when we split 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.[23] Another set of papers use a more structural approach based on the dynamic monopsony model of Manning (2003a). Ransom and Sims (2010) find an elasticity of about 3.7 for public school teachers in Missouri. Ransom and Oaxaca (2010) analyze a grocery retailer in the U.S. and their estimates range from 1.5 to 3.0 (1.5-2.5 for women and 2.4-3 for men). Hirsch et al. (2010) estimate elasticities in the range of 2-4 across a wide range of jobs and employers using linked employer-employee data from Germany. Bachmann and Frings (2017) report elasticities in the range of 1.3-3.3 for manufacturing firms in Germany. Webber (2015) estimates an average labor supply elasticity to U.S. manufacturing firms of 1.82. In that paper, manufacturing is the sector that enjoys the least wage-setting power.

Finally, two recent papers estimate labor supply elasticities using quasi-experimental evi-

[22]We choose the estimates that use materials because they are more precise (lower standard errors) compared to electricity and number of used inputs.

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

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

4.2.1 Labor supply elasticity and the minimum wage in Colombia

As highlighted above, our estimates suggest that the labor supply is relatively more elastic for lower-skilled workers in Colombia, a result that is at odds with what one would a priori expect. In this subsection, we argue that this result could indeed be rationalized by the presence of a binding minimum wage. We also provide empirical evidence consistent 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).[24]

The combination of the previous observation and the fact that minimum wages are typically more binding for lower-skilled workers, suggest that the estimated labor supply curve will be more elastic for this group of workers. We next argue that this seems to be the case in the manufacturing sector in Colombia. To that end, we briefly describe the minimum wage in Colombia and we provide some evidence consistent with our hypothesis.

Colombia has a uniform minimum wage that is adjusted on a yearly basis by a centralized bargaining process between representatives of labor unions, businesses, and the government. By law, the minimum wage should be raised to reflect the central bank inflation target for the year plus productivity changes. Since 1999, the Constitution further stipulates that yearly adjustments in the minimum wage should at least match past year's inflation. As a result, the minimum wage has increased 21% in real terms between 1998 and 2010 (Joumard and

[24] Labor unions are another type of institution that could affect the labor supply curve in a similar way as the minimum wage. In a monopsonistic market, labor unions' bargaining for higher wages can create a horizontal labor supply curve and, as a result, capture rents from employers. Although the Colombian labor legislation recognizes unions as a part of the labor relations system, its role in wage-setting matters is nowadays minimal and essentially restricted to collective bargaining at the firm-level (Agudelo and Sala, 2015). Moreover, union density in Colombia is around 4% and the coverage of collective bargaining agreements is less than 2%. Thus, we believe that this channel is less likely to be driving our results.

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).

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

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

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

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, we construct the following measure to categorize firms affected by the minimum wage: $r_{it} = w_t^{min}/\overline{w}_{it}$, where w_t^{min} is the statutory monthly minimum wage in Colombia and $\overline{w}_{it}$ is the average wage per worker. This ratio takes the value of 1 for firms paying the minimum wage to their workforce. As this ratio increases from 0 to 1, it is more likely that a firm is constrained by a minimum wage policy. Without loss of generality, we fix the control group of non-constrained firms to those with $r_{it} < 40\%$ (so that $\mathbf{1}\{\text{Binding}_{it}\} = 0$). Alternatively, we define the group of affected firms as those with the ratio above a moving threshold δ (so that $\mathbf{1}\{\text{Binding}_{it}\} = 1$). For example, $r_{it} \geq 60\%$. We then estimate equation (12) for different values of $\delta \in \{60\%, 65\%, 70\%, 75\%, 80\%, 85\%, 90\%\}$.

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 more strongly relative to firms unaffected by the policy (those with $r_{it} < 40\%$).[25]

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 unaffected 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 increasing as we get closer to 100%. For instance, when the threshold is 60%, the point estimate takes a value of 7.8, which means that the labor supply is 7.8 percentage points more elastic for firms with $r_{it} \geq 60\%$ than firms with $r_{it} < 40\%$. When the threshold is 90%, the point estimate takes a value above 20, corresponding to a highly elastic labor supply curve.

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

Furthermore, a binding minimum wage also limits the incidence of payroll taxes as employers cannot pass-through labor costs to employees as lower wages (Lee and Saez, 2012). In this context, other labor market policies, such as payroll tax cuts, can be pretty effective in boosting formal employment as shown by Kugler et al. (2017), who explore the effects of a payroll tax cut implemented in Colombia at the end of 2012. Moreover, Lee and Saez (2012) show theoretically that under a binding minimum wage, a payroll tax cut for low-skilled workers is a Pareto improving policy.[26]

Finally, it is important to note that when the minimum wage w_{it}^{min} is binding, the affected firms take the wage as given, and our measure of market power will only reflect pure *markups*. That is, the first order condition (2) from our minimization problem simplifies to $w_{it}^{min} = \lambda_{it} \times \partial Q_{it}(.)/\partial L_{it}$, and rearranging terms we get to $MU_{it} = \theta_{it}^{L}/\alpha_{it}^{L}$.[27] In this case, the minimum wage limits labor market power and the only source of market power that employers can exploit is the one in product markets. In the next section we proceed to disentangle our combined measure of market power into product and labor market power.

[25] This exercise is robust to different thresholds different than 40%.

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

[27] This is another strategy that we could use to disentangle the degree of market power in product and labor markets, and is subject of future research.

4.3 Plant-level *markdowns* and *markups*

The point estimates from the previous section suggest that there is a non-negligible degree of market power in labor markets. Using equation (5) we can translate the labor supply elasticities into *markdowns*, $MD_{it} = \epsilon_{it}^{Lw}/(\epsilon_{it}^{Lw}+1)$. Column (3) in Table 10 reports a median *markdown* of 0.89 for the pool of workers. This estimate suggests that manufacturing workers are paid a wage that is 11 percent lower than their marginal revenue product (MRPL). Column (4) and (5) show substantial heterogeneity of *markdowns* across worker types. Unskilled workers are paid 90% of MRPL, and skilled workers 77% of MRPL. Although wage setting typically takes place at the sectoral level, we do not find too much variation of elasticities across industries.[28].

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

Figure 8 shows a non-parametric relationship between *markups* and *markdowns* for different specifications. We conclude that there is a positive relationship between *markups* and *markdowns* implying that firms who exert more market power in product markets share more rents with their workers. In other words, there is a negative relationship between product and labor market power. At first, this result can be surprising, since one would expect a positive relationship of market power in both markets. However, there are potential explanations for this pattern based on the literature of productivity and agglomeration (Manning, 2010).

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

Figure 9 relates our measures of market power with labor market size finding that there is a positive relationship between *markdowns* and market size. As stated by Manning, "all labour markets are monopsonistic but less so in agglomerations". Moreover, panel B of figure 9 shows a positive relationship between *markups* and market size which confirms the point emphasized

[28] This result may be driven by the fact that we estimate labor coefficients that do not vary across sectors

by the agglomeration literature. Basically, that larger firms sort into more productive locations obtaining gains from the external Marshallian forces in big cities but at the expense of some market power. Therefore, this hypothesis could rationalize our finding of a negative correlation between market power in product vs. labor markets.

4.4 Market power and plant characteristics

We now turn to explore correlations between market power and plant characteristics.[29] We also take a step forward compared to what other people have done before and we further decompose these correlations into *markups* and *markdowns*. We run reduced-form regressions of the following form:

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

where μ can be either plant-level market power, *markup*, or *markdown*, X is a set of plant characteristics that vary across specifications as 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 and unskilled workers. Table 11 reports the results for this exercise. Column (1) displays the γ_1 point estimates for the combined measure of market power, column (2) for *markups*, and column (3) for *markdowns*.[30]

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

[29]This correlation exercise is frequently done in the IO and trade literature, see for instance DeLoecker and Warzynski (2012). We acknowledge that the correlations presented in this section are not necessarily causal and that they may be explained by time-varying unobserved heterogeneity across firms. However, we still find this exercise interesting and informative.

[30]Note that a higher *markdown* associates with lower labor market power.

5 Market power, concentration, and productivity

5.1 Market power and concentration

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

We test this hypothesis in Figure 10 by plotting the Herfindahl index on the y-axis against our three measures of market power in the x-axis.[31] Panel (a) shows a positive relationship between market concentration and aggregate market power at the industry level. In particular, a 1% increase in average market power is associated with a 0.63 p.p. increase in the Herfindahl index. Panel (b) also displays a positive relationship between average *markups* within industries and concentration. A 1% increase in *markups* is associated with a 0.60 p.p. increase in the Herfindahl index. Finally, panel (c) reports a weak positive (but not significant) correlation between market concentration and average *markdowns*.

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

5.2 Market power and productivity

This section correlates market power measures with total factor productivity and explores the implications of market power distortion on resource misallocation. We start by testing the hypothesis that market power correlates positively with total factor productivity across and within industries. We use value added per worker as a proxy for the productivity of firms.

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

In Figures 12 and 13 we break the previous results by *markups* and *markdowns*, respectively. In the case of *markups*, we find a similar result: a positive correlation between market power

[31] The unit of observation corresponds to ISIC 3 digit industries. We plot the mean for each industry across the period of analysis 2002-2012.

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

5.3 Resource misallocation

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

The main idea is that firms with higher market power than the average within the same sector produce less than the socially efficient output, while firms with lower market power produce more than the social optimum. In this sense, the measure that matters for the functioning of markets is the dispersion of market power rather than the level and this variation can come from two sources: *markups* or *markdowns*. Therefore, the goal of our application is to measure the relative TFP gains of eliminating variable market power in product markets vs. labor markets.

To that end, we estimate the implications of variable market power on TFP using the approach developed by HK. Although the analysis is similar to their paper, in the sense that variable market power is a distortion, our goal is not to measure the increase in TFP in a world with no economic distortions as they do.[32] The idea, instead, consists of estimating the relative (static) TFP gains of eliminating variable *markups* vs. removing variable *markdowns*.[33] In other words, the goal is to compare three different counterfactuals: 1) No market power distortion, 2) No *markup* distortion; and 3) No *markdown* distortion, such that we can decompose the total effect into *markups* and *markdowns*.

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

[33]By static we mean holding entry, technology, and innovation constant.

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.[34] 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. HK provide an expression for TFP at the sector level that depends on economic distortions. We rewrite this expression in the case of variable market power in product and input markets. TFP in sector s can be written as:[35]

$$\text{TFP}_s \equiv \left[\sum_{i=1}^{M_s} \left(A_{si} \cdot \frac{\overline{\text{TFPR}_s}}{\text{TFPR}_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{14}$$

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

$$\text{TFPR}_{si} \propto \frac{MU_{si}}{MD_{si}^{\theta_{L,s}}} \tag{15}$$

where MD_{si} corresponds to the *markdown* charged by firm i and MU_{si} to the *markup*. Taking into account the effect of *markups* and *markdowns* on average TFPR, we can rewrite equation (14) as:

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

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:

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

In the presence of variable market power, TFP decreases due to resource misallocation. From equation (17), it is easy to see that if there is more market power dispersion, the effect of

[34] This is an implication from the FOC of the firm optimization problem and factor price equalization.
[35] In appendix D we derive all the expressions based on HK model.

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

Table 12 shows the results of our exercise. The unit of observation corresponds to 3-digit ISIC sectors. The first row reports summary statistics of eliminating the dispersion in the combined measure of market power within sectors in Colombia.[36] On average, if we remove all variable market power TFP increases by 19.71% across sectors, the maximum increase is 49.3%, and the minimum is 6.8%.

Likewise, the second row reports the results when we eliminate the dispersion of product market power within industries. On average, there is an increase of 26.3% in TFP across 3-digit ISIC industries. The reason why the gains are higher in eliminating *markup* distortions than market power distortions is due to the negative correlation between market power in product vs. labor markets. Finally, in the third row, we run the counterfactual of removing variable labor market power. On average, TFP increases by 2.5% across sectors. These results can be aggregated to the Colombian economy using a Cobb-Douglas or CES aggregator. We conclude that dispersion in product markets is more important than labor markets for TFP and that the negative correlation between *markups* and *markdowns* correct some of the economic distortions in the economy, for instance, the aggregate TFP increases by 7%.

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

[36] This is the same counterfactual ran by HK, but instead of calling it *markup* variation, they assume that firms within the same sector face different tax schedules.

(2017) ran a similar counterfactual for the US finding that TFP may increase by 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 method developed by DeLoecker and Warzynski (2012), a labor supply choice model, and plant level production data. In a nutshell, we first obtain a combined measure of market power at the plant level using production function "proxy" methods. Then we separate this metric into *markups* and *markdowns* by estimating labor supply elasticities to the individual firm instrumenting wages with the use of intermediate inputs. With these estimates in hand, we pin down *markdowns*, and then back out *markups*.

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

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

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A Figures

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

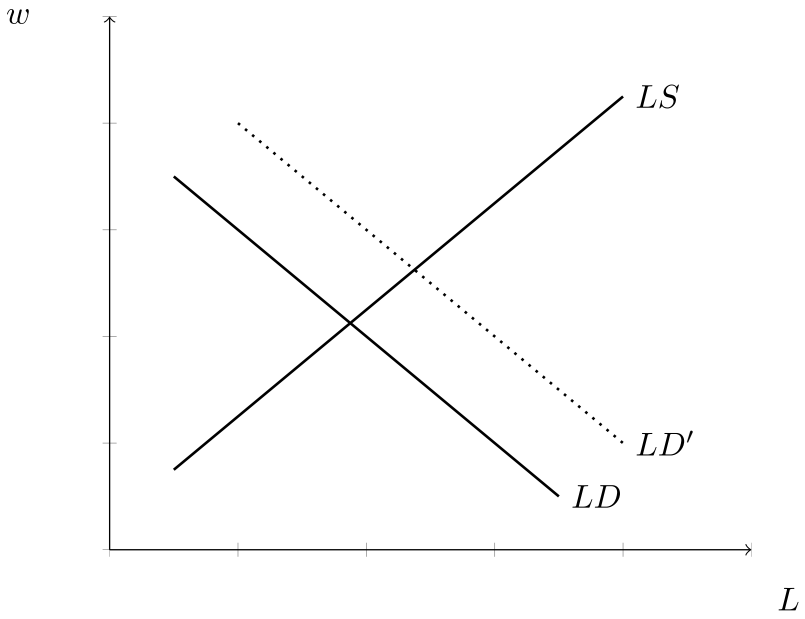


Figure 1: Identification of the labor supply to the firm

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

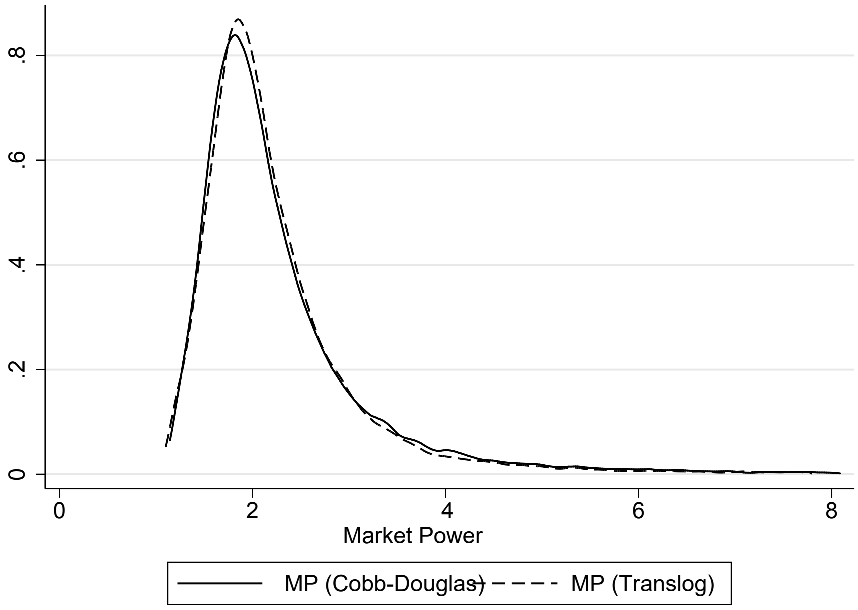


Figure 2: Distribution of market power

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

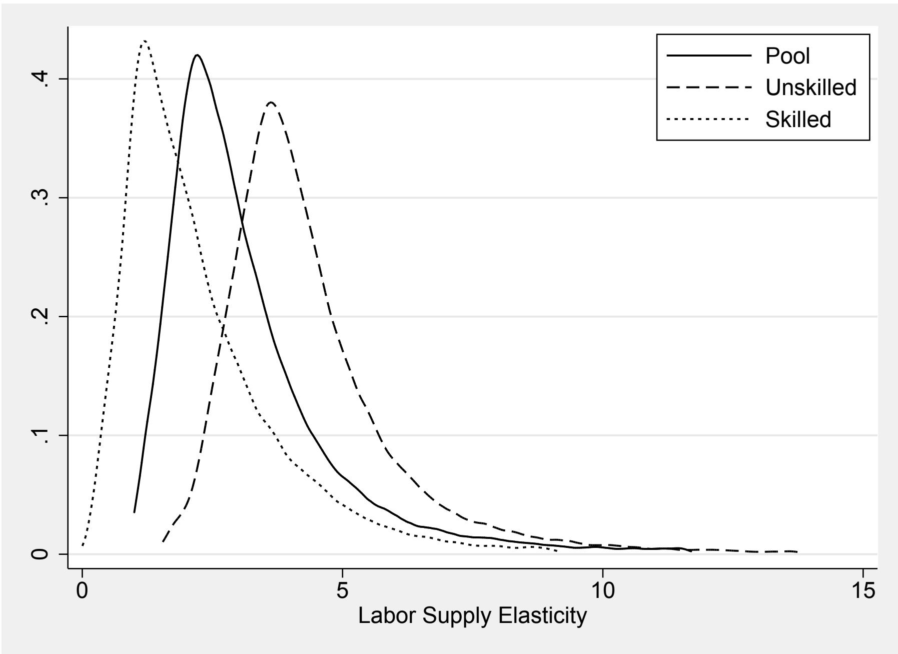


Figure 3: Distribution of labor supply elasticity to the individual firm

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.

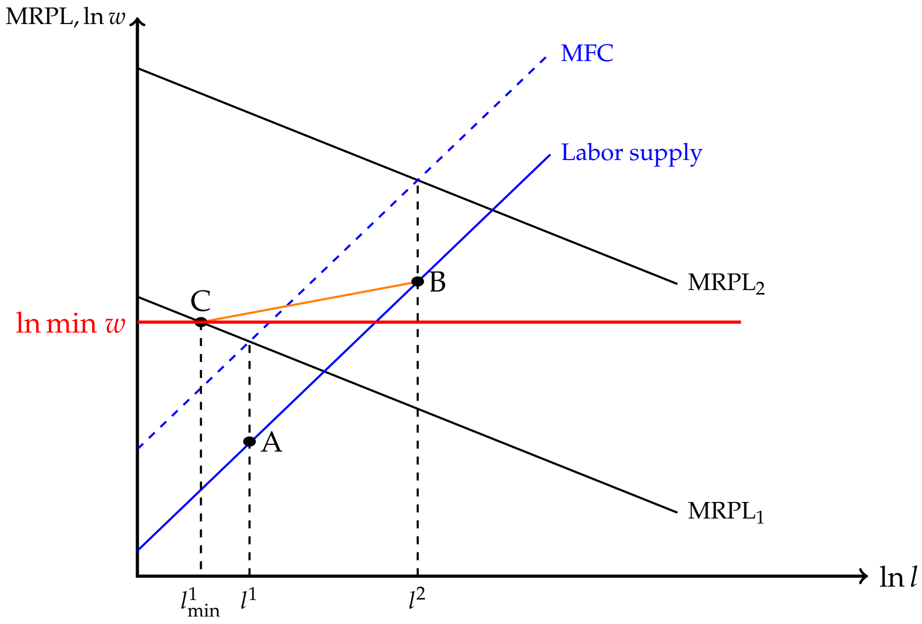


Figure 4: Binding Minimum Wage

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

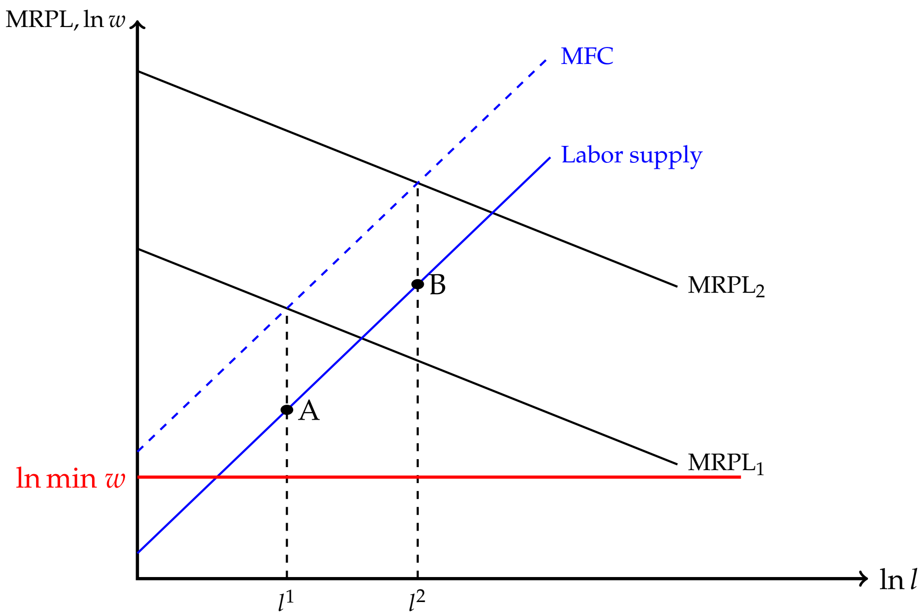


Figure 5: Non Binding Minimum Wage

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

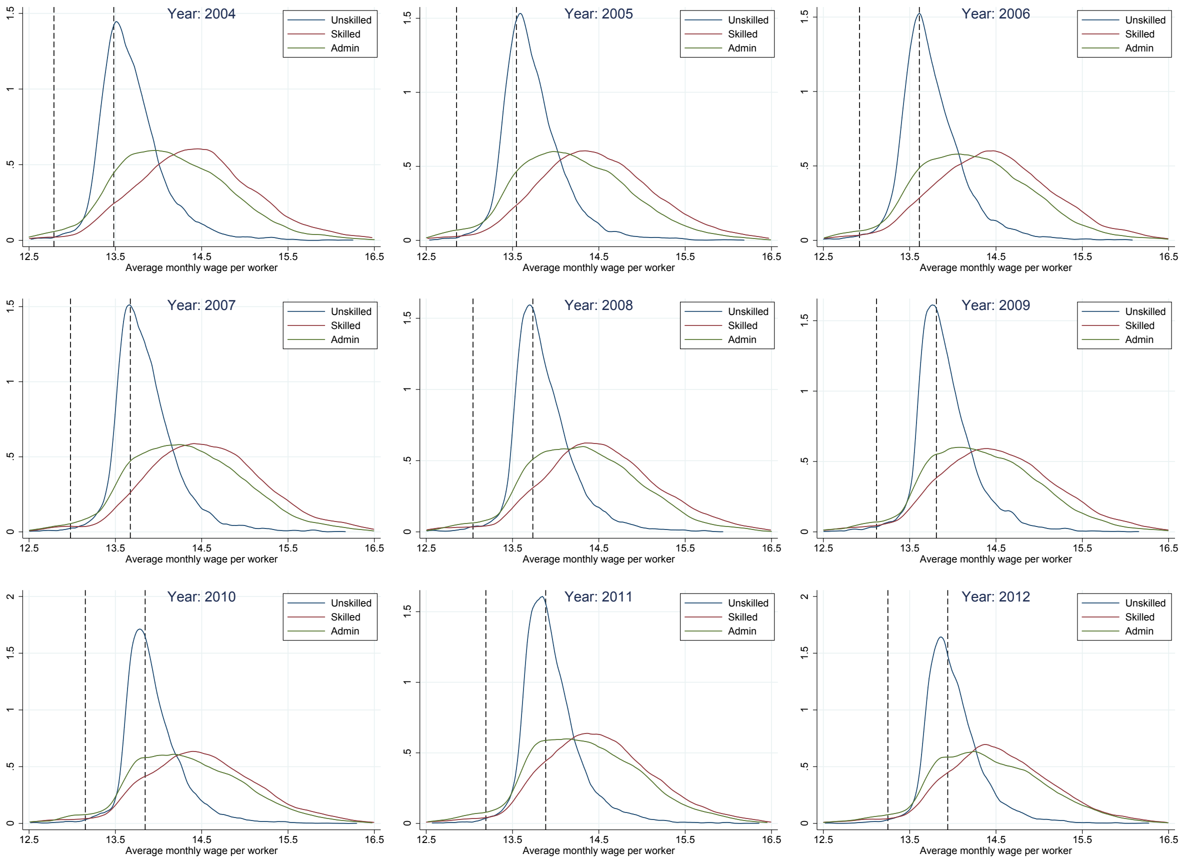


Figure 6: Distribution of average monthly (log) wage per worker in the manufacturing sector in Colombia, 2004-2012

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.

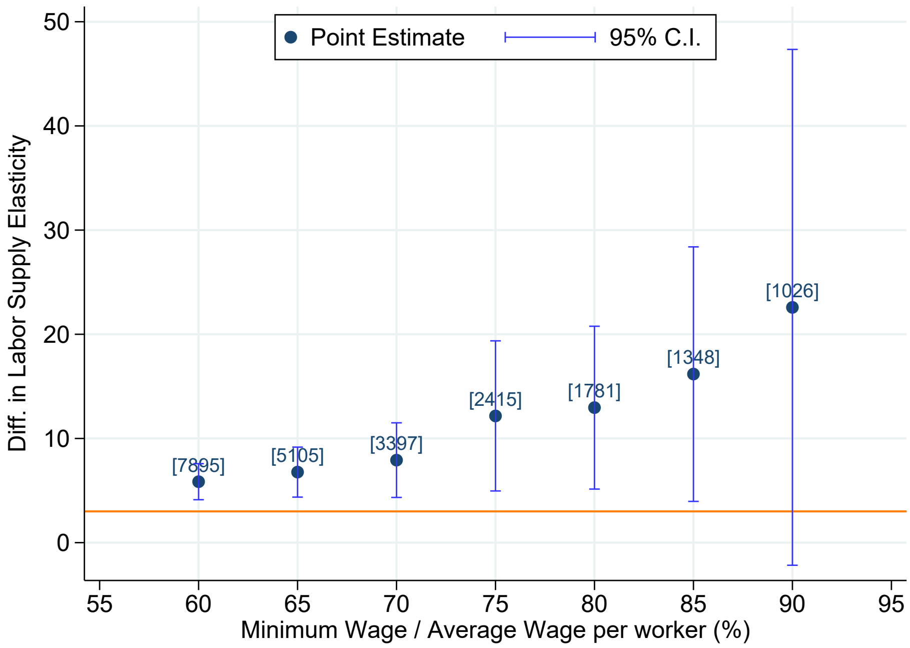


Figure 7: Labor supply elasticity and the minimum wage

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 40%). 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 in the affected group 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 40%).

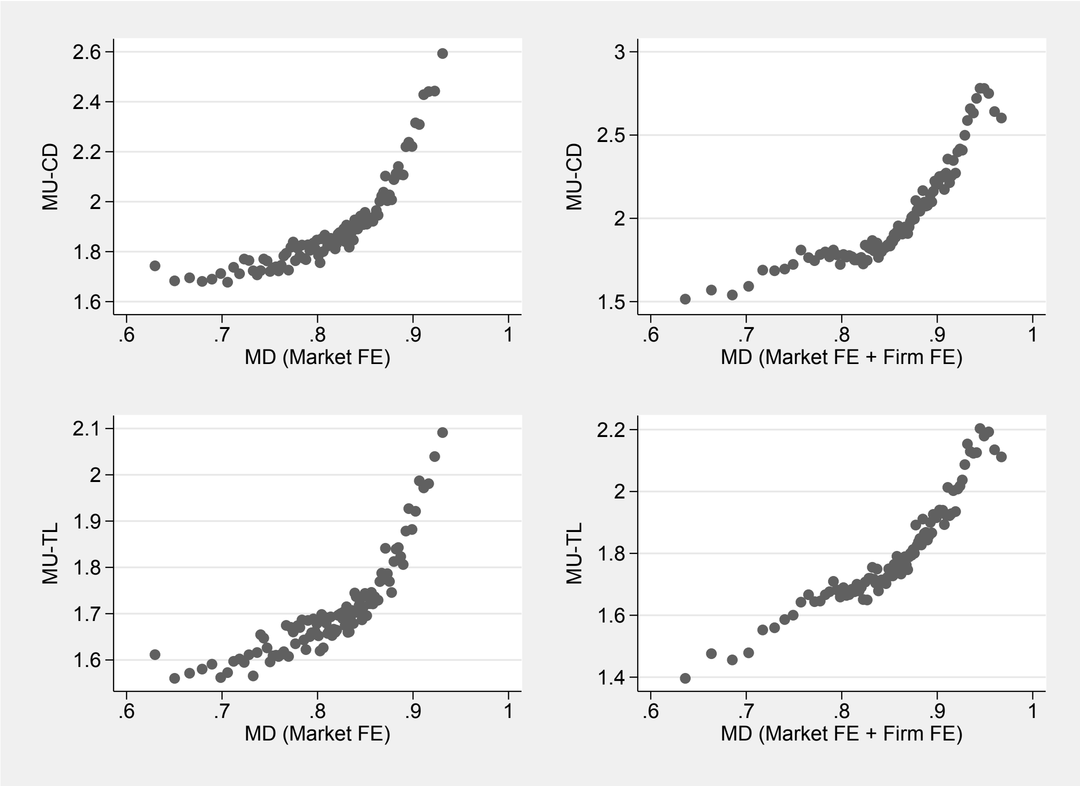
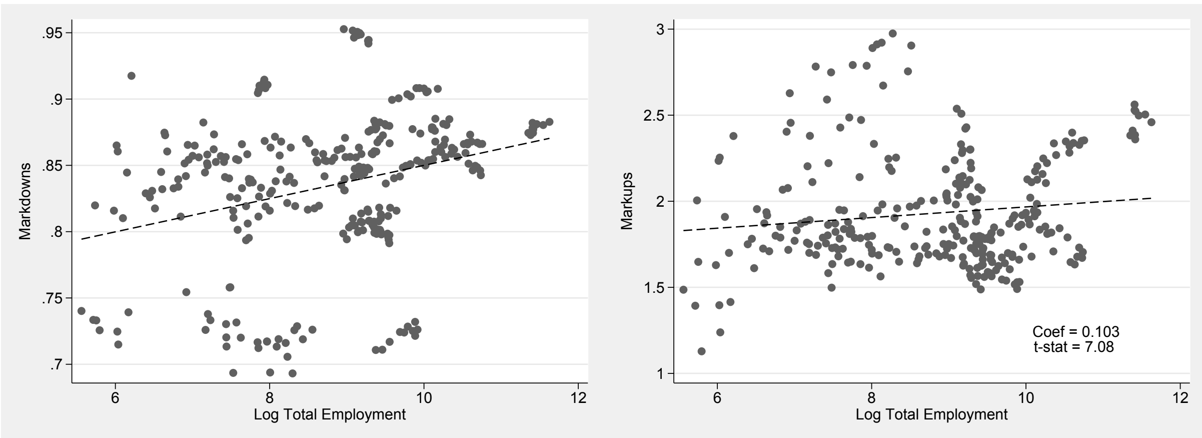


Figure 8: Correlation of *Markups* and *Markdowns*

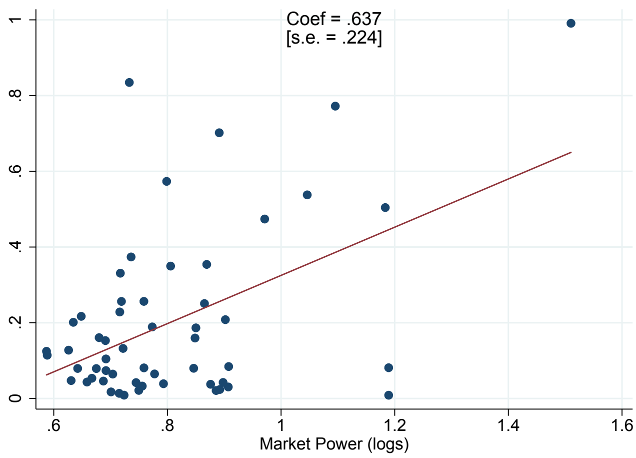
Note: this figure shows the correlation between *markups* and *markdowns*. MU-CD stands for *markups* estimated using the output elasticity of labor from the Cobb-Douglas specification. MU-TL stands for *markups* estimated using the output elasticity of labor from the Translog specification.



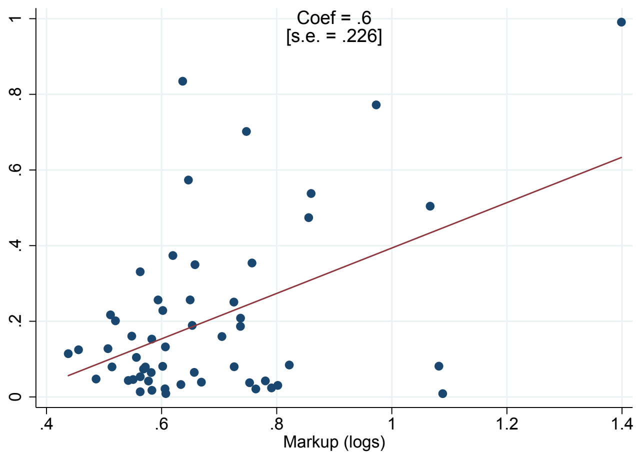
(a) Markdowns (b) Markups

Figure 9: Market Power and Market Size

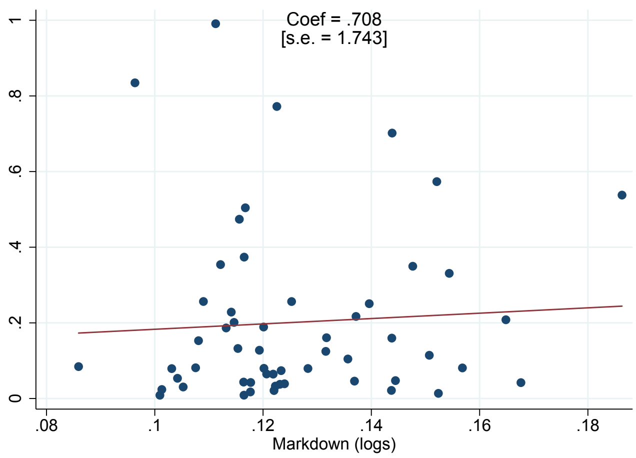
Note: This figure relates the measures of market power with labor market size computed as the log of number of workers in 3 digit isic-sector-region-year cells. The figure documents that there is a positive relationship between *markdowns* and market size, this means that labor market power is higher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



(a) Market Power



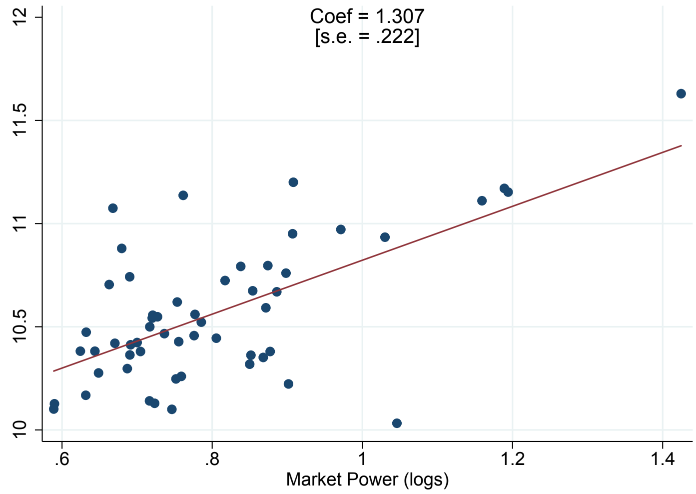
(b) Markups



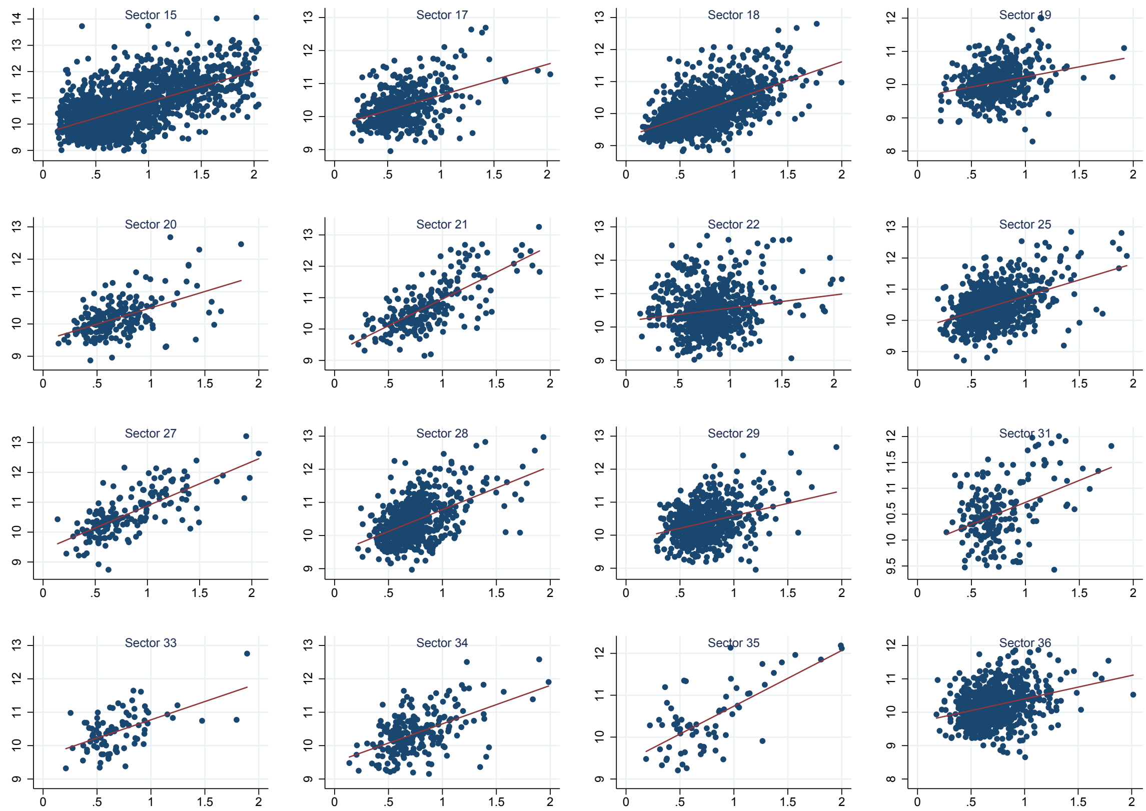
(c) Markdowns

Figure 10: Market Power and Market Concentration

Note: this figure relates market concentration to our measures of market power: combined market power (top), *markups* (middle), and *markdowns* (bottom). Market concentration is measured by the Herfindahl index using the eight largest firms in each industry.



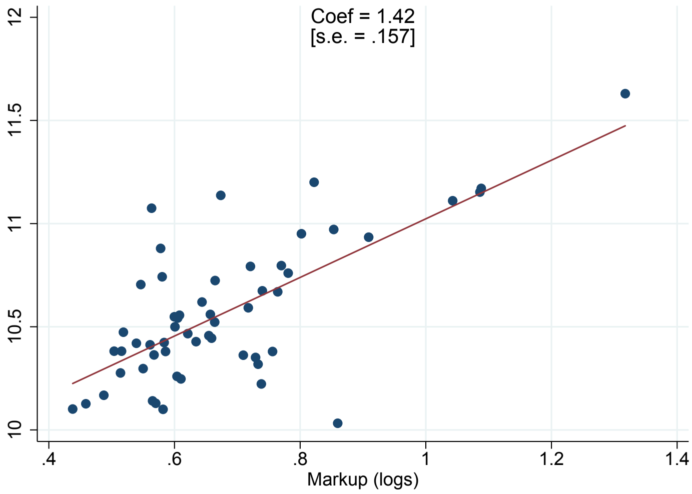
(a) Across industries



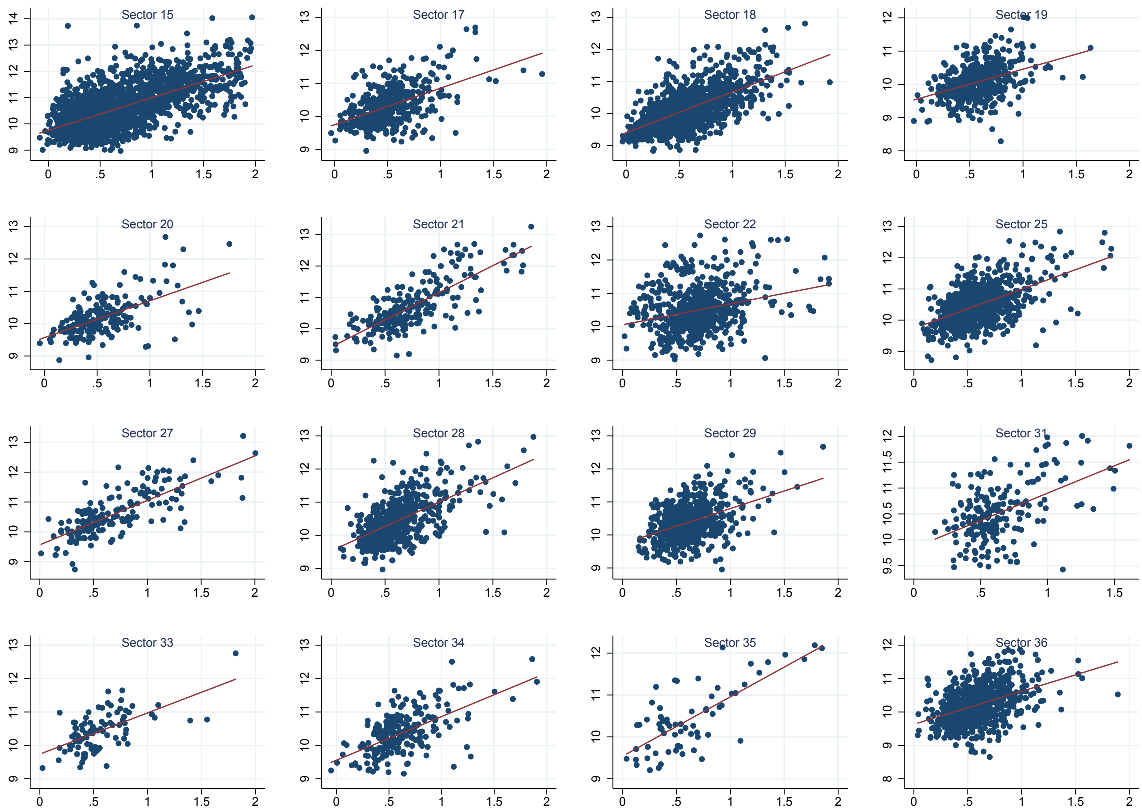
(b) Within industries

Figure 11: Productivity and Market Power

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



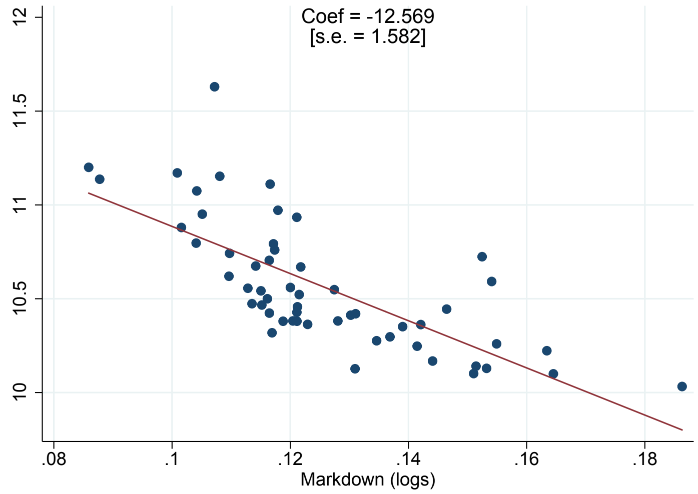
(a) Across industries



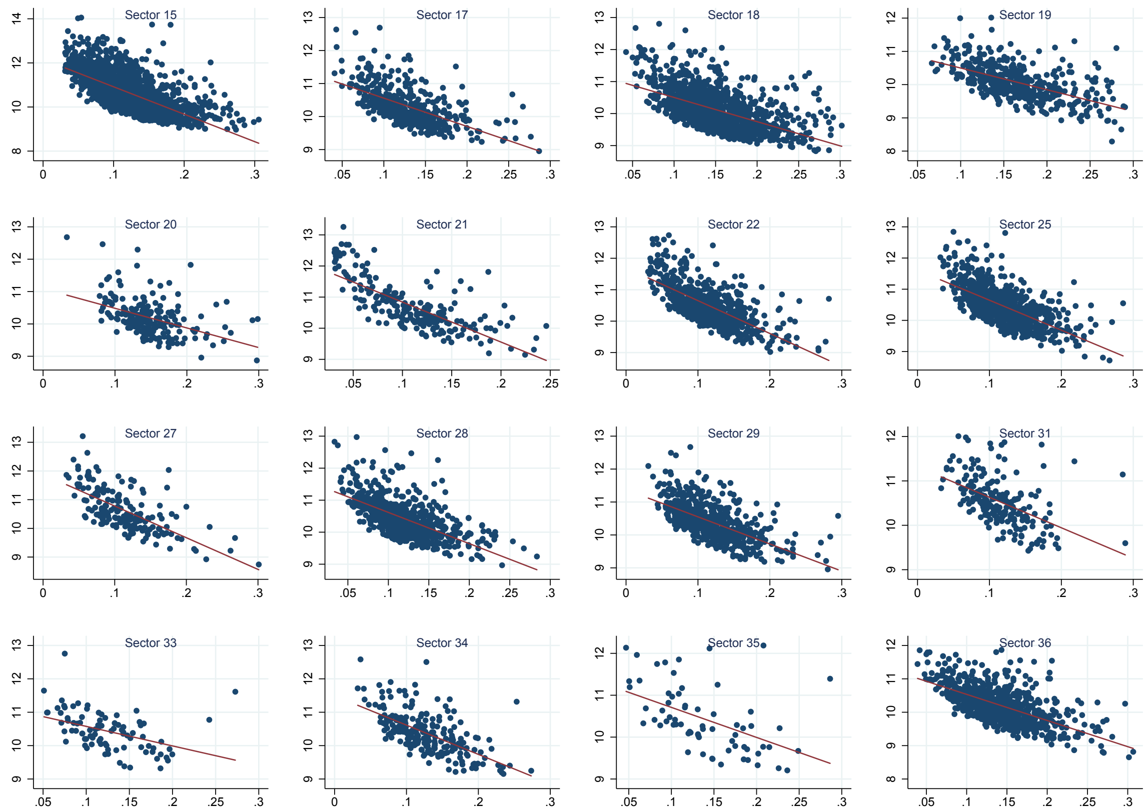
(b) Within industries

Figure 12: Productivity and *Markups*

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



(a) Across industries



(b) Within industries

Figure 13: Productivity and Markdowns

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

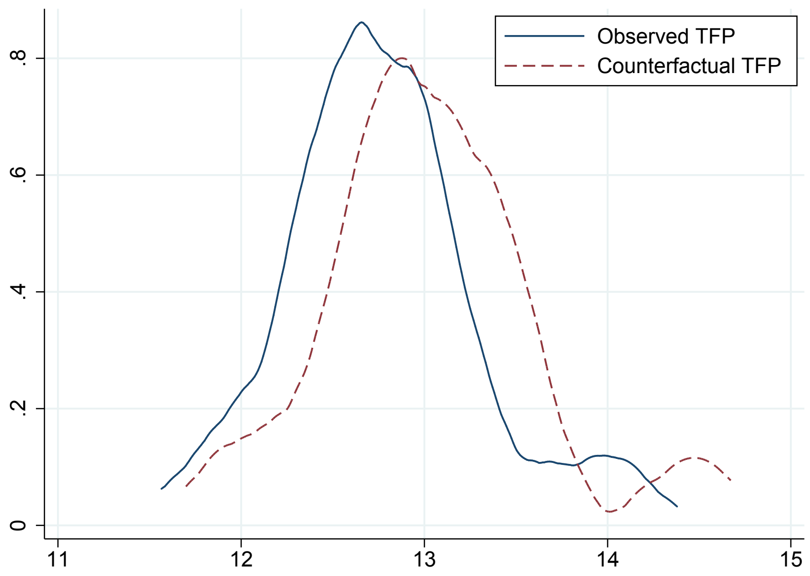


Figure 14: Distribution of total factor productivity (TFP) with variable Market Power

Note: this figure shows the distribution of total factor productivity (TFP) under variable (solid) and constant (dashed) market power. These distributions are constructed using equation (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	N	(%)	Labor share	Wagebill /VA
	(1)	(2)	(3)	(4)	(5)
Food products and Beverages	15	15743	19.60%	22.55%	0.422
Tobacco products	16	56	0.07%	0.21%	0.319
Textiles	17	3701	4.61%	7.00%	0.517
Wearing apparel, dressing and dyeing of fur	18	8285	10.31%	10.84%	0.527
Leather and leather products	19	3459	4.31%	3.21%	0.496
Wood, cork, and straw products	20	1537	1.91%	0.92%	0.509
Paper and paper products	21	2119	2.64%	3.28%	0.445
Publishing, printing and media	22	5310	6.61%	4.81%	0.482
Chemicals	24	6849	8.53%	10.31%	0.394
Rubber and plastic	25	6565	8.17%	7.88%	0.479
Non-metallic mineral products	26	4007	4.99%	5.68%	0.453
Basic metals	27	1567	1.95%	2.40%	0.477
Fabricated metal products	28	5442	6.77%	4.81%	0.499
Machinery and equipment	29	4799	5.97%	4.45%	0.515
Office, accounting and computing machinery	30	34	0.04%	0.02%	0.413
Electrical machinery and apparatus	31	1663	2.07%	2.23%	0.475
Radio, TV and communication equipment	32	185	0.23%	0.20%	0.542
Medical, precision and optical instruments	33	664	0.83%	0.56%	0.496
Motor vehicles, trailers and semi-trailers	34	1865	2.32%	2.37%	0.499
Other transport equipment	35	501	0.62%	0.87%	0.502
Furniture	36	5526	6.88%	4.93%	0.509
Total		80329		100%	0.471

Note: Summary statistics by 2-digit industry.

Table 3: Production Function Estimation

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

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

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

	First Stage		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep variable	Wage		Labor Market Share		Labor Market Share	
	Panel A: Instrument Materials (log)					
Materials (log)	2.1563***	0.3374***				
	0.0645	0.038				
Wage			0.0555***	-0.0128***	0.2007***	0.5563***
			0.000	0.000	0.001	0.006
F statistic-FS	20592	1820.44				
N	77989	77989	77989	77989	77989	77989
	Panel B: Instrument Electricity (log)					
Electricity (log)	2.4255***	0.3813***				
	0.0599	0.0512				
Wage			-	-	0.2248***	0.5746***
			-	-	0.0057	0.0789
F statistic-FS	1626.64	57.76				
N	79503	79503	-	-	79503	79503
	Panel C: Number of Inputs (log)					
Number of inputs	1.7970***	0.0978				
	0.1197	0.0952				
Wage			-	-	0.2569***	12.312
			-	-	0.0148	12.070
F statistic-FS	225.368	1.05504				
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

	First Stage		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep variable	Wage		Labor Market Share		Labor Market Share	
	Panel A: Instrument Materials (log)					
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
	Panel B: Instrument Electricity (log)					
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
	Panel C: Number of Inputs (log)					
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

	First Stage		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep variable	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 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

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

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

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

	(1)	(2)	(3)	(4)	(5)
	MP	*MU*	*MD*	*MD*-Unskilled	*MD*-Skilled
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	0.1026	0.0150
	(0.008)	(0.009)	(0.00008)
TFP (logs)	0.0660	0.7878	-0.0032
	(0.004)	(0.004)	(0.00006)
VA per worker (logs)	0.1889	0.3026	0.0225
	(0.001)	(0.002)	(0.0001)
Exporter	0.0466	0.1169	0.0310
	(0.003)	(0.004)	(0.0004)
Importer	0.1097	0.1519	0.0338
	(0.004)	(0.005)	(0.0004)
Skilled/Unskilled	-0.0055	-0.0083	0.0051
	(0.0016)	(0.0019)	(0.0001)
Observations	43,666	43,666	77,120

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

C Output Elasticity Estimation

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

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

where l is the log of labor, in this case the variable input, and k is the log of capital. For a Cobb Douglas production function we have $\beta_{ll} = \beta_{kk} = \beta_{lk} = 0$.[37] 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 materials and energy.[38] 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 the productivity level 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, $\xi_{it}(\beta)$, and form moments to obtain estimates of the production function,

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

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

[38] We include interaction of these variables and year dummy variables.

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-Klenow model with variable *markups* and *markdowns*

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

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

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:

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

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

$$Y_{si} = A_{si} K_{si}^{1-\theta_{Ls}} L_{si}^{\theta_{Ls}}, \tag{21}$$

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:

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

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

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

where MU_{si} represents the *markup* and MD_{si} the *markdown*. Therefore, with constant market power, the marginal revenue product for both inputs should be equalized across firms within the same sector. Let's define the average marginal revenue products in sector s as:

$$\frac{1}{M\bar{R}PL_s} \equiv \sum_{i=1}^{M_s} \frac{1}{MRPL_{si}} \frac{P_{si} Y_{si}}{P_s Y_s} \tag{25}$$

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

$$\frac{1}{M\bar{R}PK_s} \equiv \sum_{i=1}^{M_s} \frac{1}{MRPK_{si}} \frac{P_{si}Y_{si}}{P_sY_s} \tag{27}$$

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

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

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

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 to solve for the labor hired in sector s

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

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

$$= \theta_{Ls} \frac{P_sY_s}{M\bar{R}PL_s} \tag{32}$$

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

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

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

$$= (1-\theta_{Ls}) \frac{P_sY_s}{M\bar{R}PK_s} \tag{35}$$

Then TFP at the sector level is:

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

Finally using equations 26 and 28 we get that:

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

Plugging in P_s from equation 20 we conclude that:

$$\mathrm{TFP}_s = \frac{\left[\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\left(\frac{MD_{si}^{\theta_{L,s}}}{MU_{si}}\right)^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\left(\frac{MD_{si}^{\theta_{L,s}}}{MU_{si}}\right)^{\sigma}\right]}, \tag{38}$$

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.