Markdowns and Trade Liberalization in Developing Countries: Evidence from Colombia, 1977-2020 *

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February, 2023

Abstract

This paper estimates plant-level and aggregate markdowns in the Colombian manufacturing sector, 1977-2020, using the "production approach" with plant-level microdata. Employers exercise a certain degree of labor market power, which has increased over time. Using large-scale trade liberalization and tariff reforms as quasi-experiments, we show that the tariff reduction and increased import competition increased plant-level markdowns. The markdowns are systematically higher for skilled workers than for unskilled workers, but the effect of trade liberalization on markdowns concentrate on unskilled production workers, widening the wage gaps after the trade liberalization.

*Preliminary and incomplete. I would like to thank Costas Arkolakis, Ilse Lindenlaub, and Giuseppe Moscarini for their comments.

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1 Introduction

Economists are growingly interested in firms' labor market power and markdowns (the wedge between wages and marginal products of labor). In the U.S., employers enjoy labor market power to some extent[1], (e.g., Bassier et al. (2022), Berger et al. (2022)) and the aggregate labor market power in the U.S. manufacturing sector has been sharply increasing since the early 2000s (Yeh et al. (2022)). Yet, there is little explanation for the rise in markdowns.

This paper proposes one potential hypothesis: the increased import competition is the driver for the increasing aggregate markdowns. To do so, this paper estimates employer market power in the Colombian manufacturing sector using plant-level data and analyzes how it has changed over time after large-scale trade liberalization episodes in the 1980s and the year 2010 that plausibly offer a quasi-experimental setting. The fact that increasing import competition due to China's accession to WTO in 2001 corresponds to the period of increasing markdowns in the U.S. manufacturing sector motivates this hypothesis. [2] Colombian trade liberalization and increased exposure to import competition are comparable to or more sizable than the case in the U.S. or in other developed countries.

We first estimate plant-level markdowns by "production approach" based on De Loecker and Warzynski (2012); Yeh et al. (2022). The ratio of output elasticity with respect to labor inputs and the revenue share of labor compensation reflects the wedge between marginal products of labor and wages. The output elasticity with respect to labor is obtained using the estimation techniques from the IO literature.[3]

Evidence shows that Colombian manufacturers have labor market power, an average markdown of 1.175 and that larger plants enjoy larger markdowns on average. The aggregate markdowns have increased over time from 1977 to 2020, but the trend is not

[1]When the elasticity of the labor supply is finite, the labor market power of employers exists. There are many different mechanisms that lead to finite labor supply elasticity. Search frictions and job differentiations are the two main mechanisms widely studied in the literature.

[2]However, limited access to the U.S. administrative data prohibits the analysis in the U.S. for the time being.

[3]See Ackerberg et al. (2015), and De Loecker and Syverson (2021) to overview the literature.

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uniform, and a rise in markdowns seems to concentrate on the periods where the Colombian manufacturing sector experienced increasing import competition. In contrast, the measure of labor market concentration has a decreasing trend over time, implying that there is no clear connection between concentration and market power.

We then use the estimated plant-level markdowns to investigate the effect of trade liberalizations on markdowns. Using the quasi-experimental nature of the trade policy changes, our baseline results show that one percentage point reduction in nominal tariffs is associated with a 0.14% increase in plant-level markdowns in the trade liberalization in the 1980s and a 0.2 to 0.4 % increase in plant-level markdowns in the tariff reforms in 2010. This increase in markdowns greatly impacts wages, given the large scale of trade liberalization in Colombia. Contrary to the plant-level markdowns, labor market concentration is not associated with tariff reductions.

We also explore markdowns for different types of workers and the heterogeneous impacts of trade liberalization on their markdowns. Plant-level markdowns are consistently higher for skilled and/or administrative workers than unskilled and/or production workers. The average plant charges markdowns of more than 1.5 for the former type, while the average plant-level markdowns for the latter are around 1.17, which is close to the baseline. The effect of trade liberalization on markdowns is very different for the different types of workers. The point estimate is almost zero and statistically insignificant for effect on markdowns for skilled workers. However, the effect of tariff reduction for unskilled workers is twice as high as the baseline results with homogeneous workers. This result has an important implication for the distributional consequence of large-scale trade liberalization, widening the wage gap between skilled and unskilled workers.

This paper aims to contribute to the literature on the evolution of labor market power over time. Yeh et al. (2022) quantify the markdowns in the U.S. labor market using the "production approach" and find an increasing trend since the early 2000s. However, they do not provide sufficient reasons for the rise in markdowns in the paper. Berger et al. (2022) develop a quantitative model of labor market monopsony that links markdowns and labor market concentration and find that there is a large markdown. However, there

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is a tight connection between workers' taste for differentiated jobs and local labor market concentration in the model, and therefore, they find that the aggregate markdown has not increased over time because local labor market concentration has indeed decreased over time. This paper offers trade liberalization as a possible explanation for the recent rise in labor market power, which is not a priori linked to the measure of concentration.

Furthermore, this paper contributes to the literature on estimating labor market power in developing countries. Labor market institutions in low- and middle-income countries differ substantially from those in high-income countries. Different papers have used different empirical specifications to estimate labor supply elasticities and found a wide range of estimates, implying that labor markets might or might not be more favorable to employers than to employees. For the case of Colombia, Tartarolo and Zárate (2020) use intermediate inputs as instruments for wages to estimate labor supply elasticity and find 11% lower wages than the marginal products of labor. Amodio and de Roux (2022) use exchange rate fluctuations combined with pre-determined export destinations as a source of exogenous variation and find labor supply elasticity of about 2.5 and markdowns of about 1.4. This paper provides new estimates of labor market power for heterogeneous workers at the plant level in Colombia. The production approach circumvents the estimation of labor supply elasticity and directly obtains the plant-level markdowns for different types of workers, which allows us to investigate the plant-level response in markdowns, too.

Finally, this paper relates to the literature on trade liberalization and wage inequality in developing countries. Many developing countries have implemented trade liberalizations, and many researchers have investigated the impact of globalization on wage inequality, employment, and poverty. (e.g. Goldberg and Pavcnik (2007), Goldberg and Pavcnik (2016)) The literature so far focused on job losses due to import competition and wage changes due to reallocation, especially in a perfectly competitive labor market as in the neoclassical trade model. It has paid less attention to employers' labor market power as a source of wage inequality and poverty, although it has very different policy implications. One exception is Felix (2021) who uses the framework of job differentia-

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tion and oligopsony in Berger et al. (2022) to investigate the effect of trade liberalization in Brazil. However, due to the model's property, the only source of markdowns is workers' taste for differentiated jobs interacted with firms' local labor market concentration. Indeed, our analysis finds that the tariff reduction is not associated with the rise in labor market concentration while it increased the plant-level markdowns. This paper's use of the production approach does not assume tight theoretical links between concentration and market power.[4] The findings in this paper call for theoretical explanations that do not map labor market concentration to market power and wage markdowns.

This paper is organized as follows. Section 2 explains the data used in the empirical analysis, and Section 3 describes the empirical framework to obtain plant-level markdowns in the "production approach". We show the estimates of plant-level markdowns and the aggregate trend in Section 4. Section 5 reports the main results on the effect of trade liberalization on the plant-level markdown, and Section 6 describes the pattern in markdowns for skilled and unskilled (administrative and production) workers and how they respond to the tariff reform in Colombia. Section 7 concludes.

2 Data

The main dataset comes from the census of Colombian manufacturing plants - *Encuesta Annual Manufacturera* (EAM) - conducted annually by the National Statistical Administrative Department - *Departmento Administrativo Nacional Estadistico* (DANE). EAM covers the period 1977-2020 and the universe of manufacturing plants with ten or more workers. It contains detailed information on plant characteristics, such as the value of production, expenditures on inputs and raw materials, the number of employment, wages, investment, and capital stocks. It contains information for approximately 7,000 plants per year with unique identifiers.

However, between the years 1991 and 1992, the identifiers were reshuffled so that it is impossible to link the plants that appeared in 1991 and 1992. Therefore, we treat the

[4] But it is important to note that it makes a different assumption; the availability of one flexible input for production.

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plants before and after the year 1991 as different plants.

The other major change between 1991 and 1992 is the information on the categories of workers. Until the year 1991, the types of workers reported in the survey were skilled labor and unskilled labor, whereas the types of workers after the year 1992 were production workers and administrative workers. Most unskilled workers before 1991 were production workers who engaged in manual tasks and were therefore classified as production workers after 1992. Skilled workers are mostly white-collar workers but also include technicians and/or engineers for the production process. Similarly, some unskilled workers who engage in manual administrative jobs were classified as administrative workers, whose majority are skilled white-collar workers. Because of this inconsistency of worker classification over time, the sample is completely split before and after this change when we analyze markdowns across heterogeneous worker types.

To construct variables, we follow the literature on production function estimation. Capital, materials, and output deflators are used to construct consistent measures of inputs and outputs over time. We drop any observations with zero or negative capital, labor costs, materials, energy, or sales values. Capital variables are constructed using the perpetual inventory method. I also drop observations in the bottom 1% and top 1% of labor's share of revenue and material's share of the revenue. Raval (2022) and Demirer (2022) have detailed explanations to construct each variable.

3 Empirical Framework

3.1 Markdown Estimation

Measuring market power has been a central topic in Industrial Organization literature. The common approach relies on the specification of a demand system that governs price elasticities of demand and a supply system regarding how firms compete. Markups are obtained through the first-order condition for optimal price setting in the model. (e.g., Berry et al. (1995) Nevo (2001))

Alternatively, De Loecker and Warzynski (2012) propose the "production approach"

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to estimate markups using a first-order condition of cost minimization problem with respect to a variable input of production, which is free from frictions and statically chosen in a given period. Using production and cost data, this approach computes the plant-level markup μ_{it} as:

$$\mu_{it} = \theta_{it}^{m}(\alpha_{it}^{m})^{-1},$$

where θ_{it}^{m} is the output elasticity of such an input (raw material is often used) and α_{it}^{m} is its revenue share for a plant i at time t. The main intuition is that the wedge between marginal costs reflected in the output elasticity and the actual expenditure reflected in the revenue share of the input can reflect the market power. (See De Loecker and Syverson (2021), De Loecker et al. (2020), De Loecker and Warzynski (2012) for further discussion.)

The production approach to estimate markups has been widely used in fields outside of IO, especially international trade, labor, and macroeconomics. This paper takes this approach to estimate plant-level markdowns in Colombia. Notably, Yeh et al. (2022) extend the production approach of markup estimation to estimate plant-level markdowns in the U.S. manufacturing sectors. Since there is friction in the labor market, the ratio of output elasticity of labor and wage payment share in revenue contains both product market power (markups μ_{it}) and labor market power (markdowns ν_{it}). Specifically, we have

$$\theta_{it}^{\ell}(\alpha_{it}^{\ell})^{-1} = \nu_{it}\mu_{it} \quad \Leftrightarrow \quad \nu_{it} = \theta_{it}^{\ell}(\alpha_{it}^{\ell})^{-1}/\mu_{it} \tag{1}$$

, where markup μ_{it} is obtained by using output elasticity and revenue share of a flexible input (e.g., raw material). Similar to De Loecker and Warzynski (2012), the set of assumptions needed to estimate markdowns is the existence of at least one flexible input that is chosen statically with a given price and no adjustment costs, and this methodology inherits the measurement and identification challenges innate to the "production approach" (Syverson (2019)). [5] [6]

One may worry about the difference between revenue-based output elasticities and

[5] But Yeh et al. (2022) extensively address these problems in the paper.

[6] Azar et al. (2022) uses IO type approach to estimate labor market power in the U.S.

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quantity-based elasticities when we calculate markdowns in this approach, and it concerns because the census of Colombian manufacturing plants, as well as typical plant-level datasets in other countries, do not contain output quantity information. However, this difference does not matter for the measurement of markdowns.

First of all, wage markdown is defined as the ratio of wage to the MRL (marginal revenue of labor),

$$\nu_{it} \equiv \frac{w_{it}}{MRL_{it}}.$$

Under the assumption that the material is a flexible choice with a given price and no adjustment cost, the first-order condition of the plant's cost minimization problem implies,

$$P_{it}^M = \frac{\partial R_{it}}{\partial Q_{it}} \frac{\partial Q_{it}}{\partial M_{it}}.$$

Therefore, MRL_{it} is written as,

$$MRL_{it} \equiv \frac{\partial R_{it}}{\partial Q_{it}} \frac{\partial Q_{it}}{\partial L_{it}} = P_{it}^M \left(\frac{\partial Q_{it}}{\partial M_{it}} \right)^{-1} \frac{\partial Q_{it}}{\partial L_{it}}.$$

Using this expression, markdowns ν_{it} can be rewritten as,

$$\begin{aligned}
\frac{w_{it}}{MRL_{it}} &= \left(\frac{w_{it} L_{it}}{P_{it}^M M_{it}} \right) \left(\frac{\partial Q_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}} \right) \left(\frac{\partial Q_{it}}{\partial L_{it}} \frac{L_{it}}{Q_{it}} \right)^{-1} \\
&= \left(\frac{w_{it} L_{it}}{P_{it}^M M_{it}} \right) \left(\frac{\partial R_{it}}{\partial M_{it}} \frac{M_{it}}{R_{it}} \right) \left(\frac{\partial R_{it}}{\partial L_{it}} \frac{L_{it}}{R_{it}} \right)^{-1} \\
&= \left(\frac{w_{it} L_{it}/R_{it}}{\theta_{it}^\ell} \right) \left(\frac{\theta_{it}^M}{P_{it}^M M_{it}/R_{it}} \right) \\
&= \theta_{it}^\ell (\alpha_{it}^\ell)^{-1} / \mu_{it}
\end{aligned}$$

which corresponds to the estimation formula (1). The second equality implies that the use of revenue-based elasticities and use of quantity-based elasticities lead to the same measure of markdowns.

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3.2 Production function estimation

To estimate plant-level markdowns, we need to estimate plant-level output elasticities of a production function. Following Ackerberg et al. (2015) and De Loecker and Warzynski (2012), we have to estimate the following production function parameters β for each manufacturing sector:

$$y_{it} = f(x_{it}; \beta) + \omega_{it} + \varepsilon_{it},$$

where x_{it} is a vector of logged input variables, ω_{it} is unobserved hicks-neutral total factor productivity, and ε_{it} reflects measurement error. We use a translog production function with capital, labor, raw materials, and energy as inputs (i.e., $x_{it} = (k_{it}, \ell_{it}, m_{it}, e_{it})$). [7] Therefore, we have

$$\begin{aligned} f(x_{it}; \beta) = {} & \beta_K k_{it} + \beta_L \ell_{it} + \beta_M m_{it} + \beta_E e_{it} \\ & + \beta_{KL} k_{it} \ell_{it} + \beta_{KM} k_{it} m_{it} + \beta_{KE} k_{it} e_{it} + \beta_{LM} \ell_{it} m_{it} + \beta_{LE} \ell_{it} e_{it} + \beta_{ME} m_{it} e_{it} \\ & + \beta_{KK} k_{it}^2 + \beta_{LL} \ell_{it}^2 + \beta_{MM} m_{it}^2 + \beta_{EE} e_{it}^2. \end{aligned}$$

To deal with the endogeneity problem of unobserved productivity in the estimation, we use raw materials m_{it} as a proxy for productivity ω_{it}: $m_{it} = m_t(\omega_{it}; k_{it}, \ell_{it}, e_{it}, d_t)$. With the assumption that a plant's optimal demand for material inputs is increasing in its productivity conditional on the values of capital, labor, energy, and a year-fixed effect d_t, there exists some function $h_t(\cdot; k_{it}, \ell_{it}, e_{it}, d_t)$ such that $\omega_{it} = h_t(m_{it}; k_{it}, \ell_{it}, e_{it}, d_t)$. Consequently,

[7] We estimate gross production functions rather than value-added production functions. Ackerberg et al. (2015) and Gandhi et al. (2020) point out the identification issues of gross production function. In particular, Gandhi et al. (2020) show that the time-series variation in the prices for material inputs is critical for identification under the proxy variable methodology. The dataset in this paper spans more than 40 years, so it is plausible that there is sufficient variation in materials prices. Alternatively, Flynn et al. (2019) show that point identification is achieved when the returns to scale of the production function are known or pre-specified. On the other hand, relying on the input price variation can be problematic when there are differences in the quality of purchased inputs. Therefore, we assume constant returns to scale for the benchmark result.

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the production function can be written as

$$\begin{aligned} y_{it} &= f(x_{it};\beta) + h_t(m_{it};k_{it},\ell_{it},e_{it},d_t) + \varepsilon_{it} \\ &= \phi_t(x_{it},d_t) + \varepsilon_{it}. \end{aligned}$$

The estimation procedure consists of two stages. First, we estimate ϕ_{it} nonparametrically with a third-degree polynomial in x_{it} and obtain the fitted values $\hat{\phi}_{it}$. Secondly, by using the assumption that unobserved productivity ω_{it} follows a Markov process, $\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}$, we construct a set of moment conditions with a set of instruments to identify β:

$$\mathbb{E}(\xi_{it}z_{it}) = 0.$$

More specifically, given the candidate value of β, productivity is calculated as

$$\omega_{it}(\beta) = \hat{\phi}_{it} - f(x_{it};\beta).$$

Then, the idiosyncratic productivity shock can be constructed as a function of β:

$$\xi_{it}(\beta) = \omega_{it}(\beta) - \hat{g}(\omega_{it-1}(\beta))$$

, where $\hat{g}()$ is a third-order polynomial approximation of the function $g()$, that is obtained simply by regressing $\omega_{it}(\beta)$ on $\omega_{it-1}(\beta), \omega_{it-1}(\beta)^2, \omega_{it-1}(\beta)^3$, and a constant term. The set of instruments z_{it} is defined as the vector of one-period lagged values of every polynomial term in the translog production function, except that the current value k_{it} is used for capital. That is,

$$z_{it} = (k_{it}, \ell_{it-1}, m_{it-1}, e_{it-1}, k_{it}\ell_{it-1}, k_{it}m_{it-1}, k_{it}e_{it-1}, \ell_{it-1}m_{it-1}, \ell_{it-1}e_{it-1}, m_{it-1}e_{it-1}, k_{it}^2, \ell_{it-1}^2, m_{it-1}^2, e_{it-1}^2)$$

A standard GMM estimation is used to obtain β by minimizing a quadratic loss function for the sample analog of the moment conditions $\mathbb{E}(\xi_{it}(\beta)z_{it}) = 0$. The production parameters β are estimated for each manufacturing sector, and the corresponding output

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elasticities for labor and materials are obtained as:

$$\hat{\theta}_{it}^{L} = \hat{\beta}_L + \hat{\beta}_{KL}k_{it} + \hat{\beta}_{LM}m_{it} + \hat{\beta}_{LE}e_{it} + \hat{\beta}_{LL}\ell_{it}$$
$$\hat{\theta}_{it}^{M} = \hat{\beta}_M + \hat{\beta}_{KM}k_{it} + \hat{\beta}_{LM}\ell_{it} + \hat{\beta}_{ME}e_{it} + \hat{\beta}_{MM}m_{it}.$$

Note that the translog production function is a second-order log approximation of any arbitrary production function, and its output elasticities differ across plants with different levels of input usage. When we use the Cobb-Douglas production function, output elasticities are all constant. This specification is nested within the translog production function. As is shown later, the variance of output elasticities for labor inputs is substantial, which implies that using flexible translog specification is empirically important to capture the heterogeneity in production technology across plants.

Plant-level markups are calculated by using the output elasticity for materials $\hat{\theta}_{it}^{M}$ and the revenue share of material inputs α_{it}^{M} from the formula:

$$\hat{\mu}_{it} \equiv \hat{\theta}_{it}^{M}(\alpha_{it}^{M})^{-1}.$$

Then, plant-level markdowns are obtained by using the output elasticity for labor $\hat{\theta}_{it}^{L}$, the revenue share of labor α_{it}^{L}, and the estimated markups as:

$$\hat{\nu}_{it} = \hat{\theta}_{it}^{L}(\alpha_{it}^{L})^{-1}/\hat{\mu}_{it}.$$

4 Plant-level Markdowns and the Aggregate Trends

In this section, we present the results of the markdown estimation and the aggregate trend of labor market power in Colombian manufacturing sectors over time.

4.1 Plant-level markdowns

Table 1 summarizes the result of plant-level markdown estimation for each manufacturing sector. The average establishment charges a markdown of 1.175, and the median establishment charges a markdown of 1.075 throughout the sample period. This implies

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Table 1: Plant-Level Markdowns

Manufacturing Sector	Median	Mean	IQR_{75-25}	SD
Food, tobacco, and beverages	1.253	1.367	0.844	0.561
Textiles	1.031	1.024	0.395	0.255
Apparels	0.901	0.902	0.230	0.186
Wood products	0.947	0.931	0.151	0.141
Furniture	0.976	1.027	0.392	0.309
Paper	1.485	1.517	0.660	0.461
Printing	1.087	1.105	0.368	0.271
Chemicals	0.931	0.917	0.438	0.263
Petroleum	2.592	2.937	1.897	1.562
Rubber	1.008	1.032	0.406	0.309
Plastic	1.219	1.253	0.635	0.420
Non metal products	1.299	1.365	0.630	0.427
Iron and steel	1.046	1.061	0.446	0.322
Non-ferrous metals	2.190	2.457	1.867	1.488
Metal products	1.199	1.232	0.465	0.333
Non-electrical machinery	1.047	1.062	0.385	0.261
Electrical equipment	1.199	1.223	0.402	0.306
Automobiles and transportation equipment	1.226	1.205	0.346	0.213
Other manufacturing products	1.248	1.386	0.780	0.658
Total	1.075	1.175	0.502	0.476

that the worker receives around 85 and 93 percent of the unit value they generate in the average and median establishment, respectively.

These numbers of markdowns are smaller than the estimates from Amodio and de Roux (2022), who estimate labor market power in the Colombian manufacturing sector. They directly estimate labor supply elasticity by using a quasi-experiment and find an average plant-level labor supply elasticity of around 2.5 and a wage markdown of 1.4. However, they are larger than the estimates from Tartarolo and Zárate (2020), who show in a different empirical specification that the average workers receive 89 percent of the unit marginal value they generate. As for the U.S. manufacturing sectors, Yeh et al. (2022) find a larger average markdown of 1.53.

There is a large variation in markdowns across sectors and plants. For example, in the petroleum sector, the median plant charges a markdown of 2.59, implying that only about 40 percent of marginal products of labor are paid to workers as wage payments. Within industry, the interquartile range and standard deviation of markdowns are 0.502 and 0.476. This suggests that there is heterogeneity in markdowns across plants. Idiosyncratic factors such as firm heterogeneity in productivity, worker heterogeneity in

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human capital, and job-match heterogeneity are likely to be related to this heterogeneity in markdowns.

Table 2: Estimates of markdowns on employment size

	(1)
Employment size bin	Markdowns
less than 10	0
	(.)
10-49	0.0611
	(0.0227)**
50-99	0.173
	(0.0496)***
100-149	0.233
	(0.0583)***
150-199	0.264
	(0.0621)***
200-349	0.287
	(0.0714)***
350-499	0.323
	(0.110)***
500-649	0.287
	(0.112)**
650-799	0.194
	(0.0989)*
800-	0.285
	(0.146)*
Constant	1.068
	(0.0315)***
Observations	259762

The regression specification contains fixed effects at the region, industry, and year level.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To investigate markdown heterogeneity, we first regress plant-level markdowns on plant-level employment size, controlling the region, industry, and year-fixed effects. Employment size is categorized into ten groups according to the EAM's employment size category. [8] Table 2 documents the regression results. Markdowns increase as employment increases up to plants with 500 workers. While establishments with less than 50 workers charge almost unitary markdowns, large establishments with more than 100

[8]Although it is important to control for age to examine size effects, the information on plant age is not available consistently in the dataset. (Haltiwanger et al. (2013)) The correlation between size and age is large, and they confound one another. However, Yeh et al. (2022) show that the relationship between markdowns and plant age is not robust while markdowns are monotonically increasing in size.

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workers charge an average of 20 to 30 percent higher markdowns. In such establishments, a worker receives only 77 percent of the marginal products of labor they produce.

Next, following Yeh et al. (2022), we conduct variance decomposition analysis. In natural logs, markdowns are additively separable as

$$\ln(v_{it}) = \ln(\theta^{\ell}_{it}) - \ln(\alpha^{\ell}_{it}) - \ln(\mu_{it})$$

where θ^{ℓ}_{it} is the plant-level elasticity of output with respect to labor, α^{ℓ}_{it} is a revenue share of labor, and μ_{it} is the markup in the product market. Therefore, the variance of markdowns is decomposed as

$$\begin{aligned} V(\ln(v_{it})) &= V(\ln(\theta^{\ell}_{it})) + V(\ln(\alpha^{\ell}_{it})) + V(\ln(\mu_{it})) \\ &\quad - 2[Cov(\ln(\theta^{\ell}_{it}), \ln(\alpha^{\ell}_{it})) - Cov(\ln(\alpha^{\ell}_{it}), \ln(\mu_{it})) + Cov(\ln(\theta^{\ell}_{it}), \ln(\mu_{it}))] \end{aligned}$$

Table 3 shows which term is important to account for the variance of markdowns. Heterogeneity in markdowns is largely explained by heterogeneity in output elasticity and revenue share rather than heterogeneity in markups. The variances of output elasticity and revenue share are more than twice as large as that of markdowns.

Table 3: Variance decomposition of markdowns

		Variance
Markdown	ν_{it}	0.134
Elasticity	θ^{ℓ}_{it}	0.231
Revenue share	α^{ℓ}_{it}	0.437
Markups	μ_{it}	0.092
		Covariance
	θ^{ℓ}_{it}, α^{ℓ}_{it}	0.264
	α^{ℓ}_{it}, μ_{it}	-0.016
	θ^{ℓ}_{it}, μ_{it}	0.033

This finding highlights the importance of our translog production function specification. If we use the Cobb-Douglas production function, the variance of output elasticity is zero by construction, and as a result, one may miss the main determinants of markdown variation in analysis.

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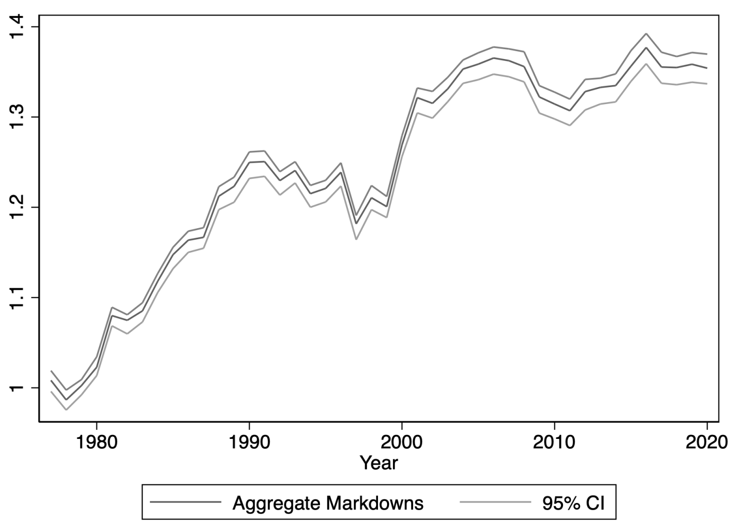
4.2 Trends in Aggregate Labor Market Power

In this subsection, we investigate time trends in aggregate markdowns to see whether labor market power in the Colombian manufacturing sector has increased over time. Following De Loecker et al. (2020) for the calculation of aggregate markups in the U.S., aggregate markdowns are obtained as weighted averages based on sales: [9]

$$\mathcal{V}_t = \sum_{i \in P_t} \omega_{it} v_{it}$$

where P_t denotes the set of active plants in year t and ω_{it} is a sales-weight of plant i.

Figure 1: The Evolution of Aggregate Markdown



Note: The confidence interval for the aggregate markdown is calculated by the nonparametric bootstrap procedure with 200 simulations.

Figure 1 illustrates the resulting time trend of aggregate markdowns $\mathcal{V}_t$. The aggregate markdowns have increased over time from 1977 to 2020. There is a large increase in aggregate markdowns in the 1980s and the early 2000s. From 1980 to 1990, the aggregate markdowns went up from 1.02 to 1.25. After the declining trend in the 1990s, it increased again from 1.20 in 1999 to 1.32 in 2001. After this jump, the aggregate markdowns have stayed constant, with a small drop during the financial crisis followed by a slight increase

[9] Yeh et al. (2022) use a different formula to obtain aggregate markdowns. They use a weighted harmonic average to obtain markdowns at the local labor market level. Then they take a weighted average of them. We also calculated the aggregate markdowns using their formula and obtained the same trend over time.

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after the year 2010.

The stark increase in the aggregate markdown in the early 2000s is observed in the U.S. manufacturing sector, too. In the baseline calculation of Yeh et al. (2022), they show that the aggregate markdown went up around 20 % in the 2000s. Although they did not provide explanations for possible mechanisms behind it, this period corresponds to the sharp increase in import competition from China. This motivates analysis for the following section. In the Colombian case, there were a large trade liberalization in the 1980s and the tariff reform in 2010. During these periods, the aggregate markdowns have increasing trends. We show that tariff reductions are associated with the rise of plant-level markdowns and, thus, the aggregate markdowns in Section 5.

Measures of market concentrations are widely used as proxies for market power. The Herfindahl-Hirshman index (HHI) is a canonical measure to summarize the level of concentration either in the output or input market, and it has gained popularity in research on labor market power. Especially, Berger et al. (2022) construct the model of labor market oligopsony, which is a labor market counterpart to Atkeson and Burstein (2008), and show that Herfindhal indices of payroll are sufficient statistics to measure aggregate labor market power. Using their model, Felix (2021) shows that Brazilian trade liberalization increased firms' labor market power because of higher labor market concentration. However, concentration is not necessarily a synonym for market power. To see this, we compare these two by calculating the HHI for labor markets in a standard way:

$$HHI_{mt} = \sum_{i \in P_{mt}} \left(\frac{L_{it}}{L_{P_{mt}}} \right)^2 \quad \text{where} \quad L_{P_{mt}} = \sum_{i \in P_{mt}} L_{it},$$

, P_{mt} is a set of plants in a market m at time t, and L_{it} is a plant-level employment. The aggregate HHI is calculated as a weighted average of market-level HHI using market-level employment as weight. Each market is defined as region-product (ISIC four-digit level) for the main specification. Although each region might be bigger than the usual notion of commuting zones, detailed plant location information is unavailable. When a market is defined as a national industry as in Autor et al. (2020) or defined at ISIC three-digit industry level, the qualitative results below do not change.

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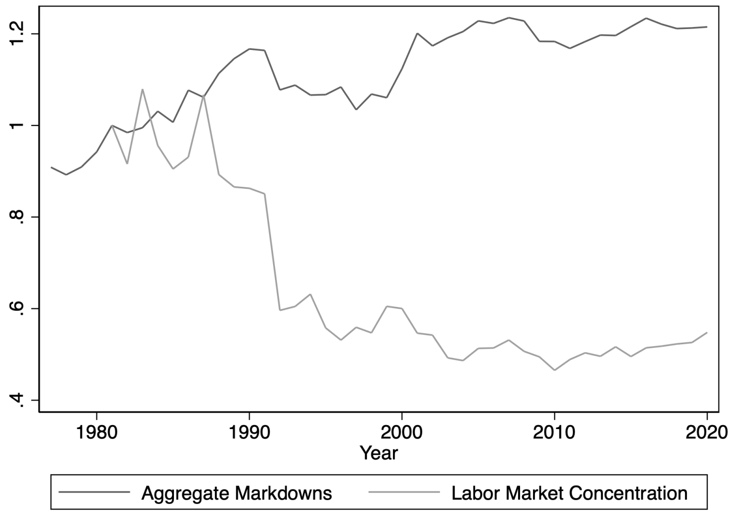
Figure 2: Aggregate Markdowns and Labor Market Concentration



Note: The levels in 1981 are normalized to one. The market concentration index is available from 1981 due to the availability of plant region information.

Figure 2 plots the evolution of aggregate markdowns and the concentration index. They are normalized to 1 in 1981. [10] There is a huge drop in labor market concentration between the late 1980s and the early 1990s, and it has been stable afterward. For some periods, the concentration measure and aggregate markdowns have the same trend, especially in the 1990s and the 2010s, but there is a negative relationship in the late 1980s and the 2000s. These patterns suggest that market concentration does not always correspond to labor market power and thus does not work as sufficient statistics for the aggregate markdowns.

5 Trade liberalization

In this section, we analyze the effects of trade liberalization in Colombia on plant-level markdowns. Colombia experienced two large-scale trade reforms in the 1980s and in 2010, and their tariff reforms are arguably quasi-experiments that enable us to study the effects of tariff reductions on the labor market outcomes.

[10]The location information is available since 1981.

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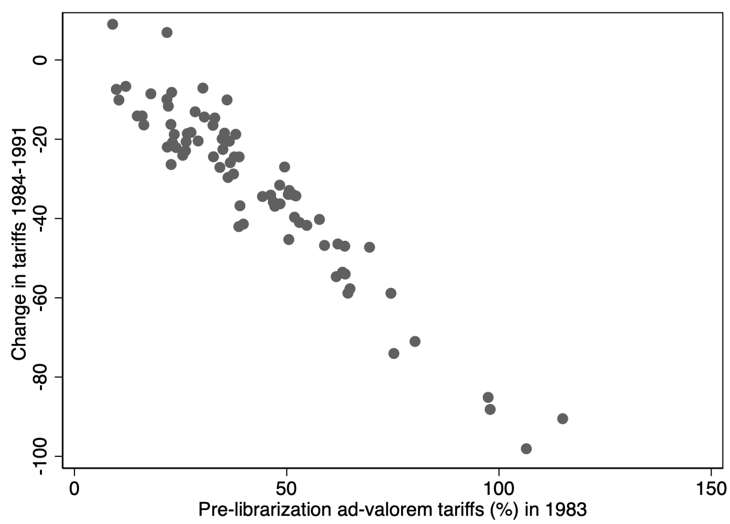
5.1 Early trade liberalization in Columbia, 1984-1991

Between 1985 and 1991, Colombia reduced tariff and non-tariff barriers after decades of import-substitution policies and increased protection during the early 1980s. While manufacturing sectors enjoyed high levels of protection with an average tariff of 50 %, it dropped from 50% to 13% from 1985 to 1991. There were large tariff variations over time and across sectors, and tariff reductions in that period and initial pre-liberalization tariff rates have a strong relationship. This episode of trade liberalization has been widely used to evaluate the effects of trade liberalization in the context of developing countries. (For example, Goldberg and Pavcnik (2005) and Attanasio et al. (2004))

Figure 3: Tariff decline 1984-1991 and pre-liberalization tariffs in 1983



Note: Each dot represents one product from ISIC code at four-digit level.
Source: Departamento Nacional de Planeación

Figure 3 shows the strong negative relationship between the 1984–1991 tariff changes and the initial, pre-liberalization tariff rates. The most protected product categories in 1983 faced a tariff rate of more than 100%, but the change in tariffs for such sectors was substantial and the rate dropped by almost 100 %. In contrast, for the least protected product categories, there was little change in their tariff rates during the period.

The empirical approach relates the change in the plant-level markdowns before and after the trade liberalization to changes in tariff rates in percentage points. In particular,

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Table 4: Plant-level markdowns and tariff reductions, 1984-1991

Change in markdowns	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Tariff changes	-0.00139	-0.00132	-0.00110	-0.00105	-0.00106	-0.000844
	(0.000457)***	(0.000446)***	(0.000437)**	(0.000399)***	(0.000394)***	(0.000386)**
Industry FE	YES	YES	YES	YES	YES	YES
Size Control	NO	YES	YES	NO	YES	YES
Region FE	NO	NO	YES	NO	NO	YES
Observations	2519	2519	2519	2519	2519	2519

Standard errors are clustered at an industry level and reported in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

we estimate the following equation:

$$\Delta \ln(v_{i,84-91}) = \beta_0 + \beta_1 \Delta T_{s(i),84-91} + X\gamma + \varepsilon_i. \tag{2}$$

where $\Delta T_{s(i),84-91}$ is a tariff change in a product category s to which a firm i belongs and X is a vector of controls.

Table 4 reports the estimation results. Column (1) shows the effect of the tariff reduction on the change in the plant-level markdowns, which is negative and statistically significant. A one percentage point more tariff reduction is associated with a 0.14 percent increase in plant-level markdowns. The average tariffs in the whole manufacturing sector dropped from 50% to 13% between 1984-1991. Based on the estimation results, a 37 percentage points tariff reduction is associated with an increase in plant-level markdowns by 5.18 percent. Starting from the average plant-level markdown of 1.175, this increase leads to a markdown of 1.236. As a result, the shares of marginal products of labor that a worker receives fall from 0.851 to 0.809.

Column (2) controls plant size, and Column (3) controls region-fixed effects. The estimates do not change much, and the effects are both statistically significant. Column (4) to (6) contains the 2SLS estimates using pre-liberalization tariff levels as an instrument for the tariff changes. The estimated effects become smaller from 0.139 percent to 0.105 percent, comparing Column (1) and Column (4), but the effects are negative and

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Table 5: Labor market concentration and tariff reductions, 1984-1991

Change in HHI	(1) National OLS	(2) National IV	(3) Local OLS	(4) Local OLS	(5) Local IV	(6) Local IV
Tariff changes	-0.000895	-0.000766	-0.000432	-0.000463	-0.000206	-0.000243
	(0.000552)	(0.000573)	(0.000466)	(0.000471)	(0.000491)	(0.000484)
Region FE	-	-	NO	YES	NO	YES
Observations	76	76	530	530	530	530

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

statistically significant.

To relate the change in markdowns to the change in market concentrations, we regress the change in the HHI for labor markets on the tariff changes as in equation (2). Table 5 shows the results. Neither national labor market concentration nor local labor market concentration is associated with the tariff change. The estimated coefficients are small and not statistically significant for all specifications using pre-liberalization tariff levels as instruments or with regional fixed effects for local labor market concentration. These findings indeed contrast with the findings from Brazilian trade liberalization. Felix (2021) finds that tariff reductions in Brazil increased firms' monopsony power because the labor market concentration increased. This implies that the findings in the Colombian manufacturing sector contrast with a Cournot oligopsony model with job differentiations, and the market concentration index does not work as sufficient statistics for the change in plant-level markdowns, as mentioned in Section 4.

5.2 Late trade liberalization episode: the tariff reforms in 2010-2011

There are only a few studies that used the tariff reform that took place in 2010. The purpose of this reform was to simplify customs administration by reducing tariff dispersion and speeding up economic growth, generating more employment and reducing poverty, according to the Ministry of Commerce, Industry, and Tourism. Import tariffs are set to 15% for consumer goods, 10% for raw materials and capital for agriculture, or 5% for raw materials and capital goods for industrial use. Such adjustments reduced the average nominal tariff from 12% to 8%, and the change in tariff schedules was highly cor-

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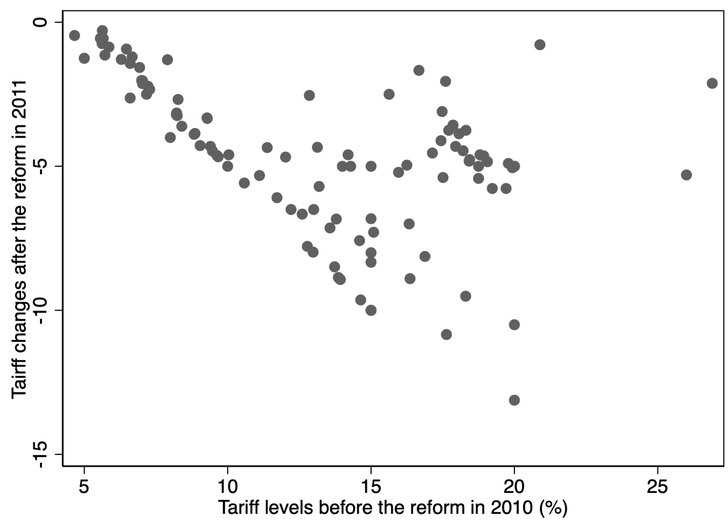
related with the levels before the reform and orthogonal to other sectoral shocks (see Meleshchuk and Timmer (2020)). This implies that the reform was not to protect specific industries but to reduce the dispersion in tariffs for all goods simply.

Figure 4: Tariff decline due to the 2010 reform and tariff levels before the reform



Note: Each dot represents one product from ISIC code at four-digit level.
Source: Departamento Nacional de Planeación

Figure 4 plots the relationship between tariff levels in 2010 and the change in tariffs between 2010-2011 due to the tariff reform. The good-specific reduction in tariffs in 2011 was highly correlated with the pre-reform level of the tariffs.

Unlike the early episode of trade liberalization in the 1980s, this reform took place only within a year, and tariff levels after the reform have remained constant. Therefore, we can identify the dynamic effects of tariff reductions by using the following cross-sectional regressions:

$$\ln(v_{it}) - \ln(v_{i,2010}) = \beta_0 + \beta_1 \Delta T_{s(i),2010-2011} + X\gamma + \varepsilon_i \tag{3}$$

where t takes the years 2008, 2009, 2011, 2012, 2013, 2014, 2015, and 2016, and $\Delta T_{s(i),2010-2011}$ is the changes in the tariffs between 2010 and 2011 for the product category to which the plant i belongs.

Figure 5 shows the coefficient for the change in plant-level markdowns and 90% confidence intervals from the regressions. The changes in markdowns between 2008-2010

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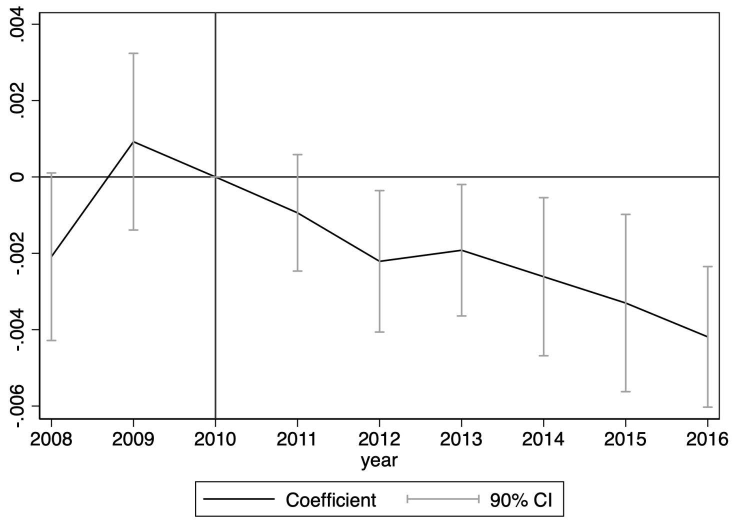
Figure 5: Dynamic response of plant-level markdowns to the 2010 tariff reform



Note: This figure plots the estimated coefficients of a regression equation with 90% confidence intervals. The left-hand side variable is the log difference between markdowns in year t indicated on the horizontal axis and markdowns in 2010. All the regressions include controls for industry-fixed effects, plant employment size, and region-fixed effects.

and between 2009-2010 are not statistically significant and, thus, not associated with the tariff reduction in 2010. This result can be interpreted as a placebo test. Although the change in markdowns after the reform was not immediate, the effect of the tariff reform on plant-level markdowns is statistically significant after 2012. One percentage point reduction of import tariffs is associated with a 0.2 percent increase in markdowns in 2012 and a 0.4 percent increase in 2016. The effect of tariff changes is larger than the effect of the early trade liberalization in the 1980s, but the average tariff change due to this reform was from 12% to 8%. Therefore, the effects on plant-level markdowns are small on average.

Similar to the case of the early trade liberalization, we estimate the effect of the tariff reform on the labor market concentration by replacing the left-hand side of equation (3) with national and local HHIs. Figure 6 plots the coefficient for the change in national labor market concentration (Left) and local labor market concentration (Right). The estimated coefficients are small and not statistically significant. The dynamic response is slightly increasing over time, which implies that the tariff reform reduced the concentration, although the estimated coefficients are all statistically insignificant. This finding

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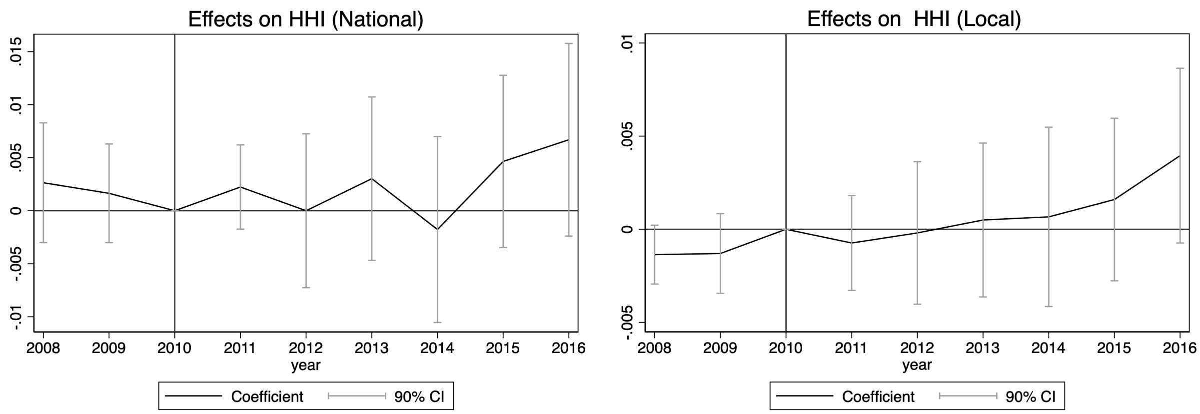
confirms the results of the early trade liberalization and that the increase in markdowns is not associated with market concentration.

Figure 6: Dynamic response of labor market concentration to the 2010 tariff reform



Note: These figures plot the estimated coefficients of a regression equation with 90% confidence intervals. The left-hand side variable is the difference between HHI in year t indicated on the horizontal axis and HHI in 2010.

In sum, the results from both the early and late trade liberalization suggest that plants that have been more exposed to the decline in tariffs and increased import competition increased their markdowns more than other plants, while labor market concentration in more affected sectors did not change much compared with less affected sectors before and after the tariff reductions.

6 Heterogeneous Labor

6.1 Plant-level markdowns

This section investigates the heterogeneity in plant-level markdowns across two types of labor. As mentioned in Section 2, the EAM changed the classification of workers in 1992. From 1977 to 1991, we have skilled and unskilled workers, whereas from 1992 to 2020, we have production and administrative workers. We split the sample before and after 1992 and estimate the translog production function with five inputs(capital, skilled(administrative) workers, unskilled(production) workers, raw materials, and energy). Plant-level markdowns for each worker type are obtained using the estimates of

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output elasticities and observed revenue shares of compensation for each worker category.

Table 6: Plant-Level Markdowns (Heterogeneous labor): 1977-1991

	Mean Markdowns	
	Skilled	UnSkilled
1977	1.423	1.011
1978	1.420	1.006
1979	1.464	1.033
1980	1.501	1.063
1981	1.603	1.123
1982	1.566	1.112
1983	1.571	1.128
1984	1.659	1.173
1985	1.661	1.206
1986	1.664	1.212
1987	1.674	1.219
1988	1.757	1.280
1989	1.767	1.306
1990	1.803	1.333
1991	1.801	1.347
Total	1.628	1.175

Table 6 shows mean estimated markdowns by year for skilled and unskilled workers between 1977-1991. First and foremost, allowing for labor heterogeneity reveals the heterogeneity in markdowns for different skill groups. Markdowns for skilled workers are much higher than the baseline in Table 1. During the sample period between 1977-1991, the average plant charges a markdown of 1.628, and a skilled worker receives 64 percent of the marginal products of labor they produce. On the other hand, markdowns for unskilled workers correspond closely to the baseline.

Table 7 shows mean estimated markdowns by year for administrative and production workers between 1992-2020. The pattern of markdowns is similar to Table 6. Markdowns for administrative workers are much higher than those for production workers.

It is noteworthy that there is no such difference in markdown estimates from Yeh et al. (2022) for production and nonproduction labor in the U.S. manufacturing sectors. They find little evidence of any systematic difference in markdowns between the two groups and argue that production and nonproduction workers in the U.S. are not synonyms for low- and high-skill workers, and the U.S. production workers include many

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Table 7: Plant-Level Markdowns (Heterogeneous labor): 1992-2020

	Mean Markdowns	
	Administrative	Production
1992	1.990	1.159
1993	2.008	1.169
1994	1.907	1.161
1995	1.839	1.162
1996	1.814	1.175
1997	1.738	1.153
1998	1.728	1.171
1999	1.692	1.170
2000	1.830	1.189
2001	1.879	1.201
2002	1.871	1.202
2003	1.923	1.208
2004	2.007	1.214
2005	2.009	1.203
2006	2.034	1.202
2007	2.030	1.212
2008	1.966	1.202
2009	1.916	1.176
2010	1.928	1.176
2011	1.935	1.172
2012	1.966	1.184
2013	1.924	1.192
2014	1.910	1.196
2015	1.891	1.210
2016	1.911	1.214
2017	1.836	1.214
2018	1.846	1.217
2019	1.828	1.224
2020	1.742	1.220
Total	1.893	1.190

highly-skilled craftspersons, inspectors, and product developers. In addition, Azar et al. (2022) find little difference in labor market power between higher- and lower-paying occupations.

This does not seem to be the case in Colombia. Unskilled and/or production workers are subject to much lower markdowns. It is plausible that markdowns are lower because low-skilled workers should have a much easier time finding outside employment options. Some possible reasons for it are that their tasks are more general than skilled and/or administrative workers and that there are many more alternative opportunities for employment.

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Table 8: Plant-level markdowns and tariff reductions, 1984-1991

Change in Markdowns	(1) Skilled OLS	(2) Unskilled OLS	(3) Skilled IV	(4) Unskilled IV
Tariff Changes	-0.000346	-0.00222	-0.0000431	-0.00228
	(0.000618)	(0.000821)***	(0.000651)	(0.000778)***
Industry FE	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	2100	2100	2100	2100

Standard errors are clustered at an industry level and reported in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2 The effect of tariff changes on markdowns

To see the heterogeneous effects of trade liberalization on markdowns for different worker types, we run the same regressions in Section 5.

Table 8 summarizes the results for Equation (2). Columns (1) and (3) show the results for skilled labor and Columns (2) and (4) show the results for unskilled labor. Pre-liberalization tariff level is used to instrument the tariff changes for Columns (3) and (4).

The effect of the tariff changes on markdowns for skilled labor is very small and statistically insignificant. The point estimates are of smaller order than in Table4. In contrast, the plant-level markdowns for unskilled workers increased after the trade liberalization. The point estimates are negative and statistically significant. Comparing Column (2) (-0.0022) with Column (3) of Table4 (-0.0011), the effect is twice as large for unskilled workers as in the specification of homogeneous labor. When we pool heterogeneous workers, the the estimated effect of tariff reduction on unskilled workers is mitigated because of smaller effects on skilled workers.

Figure 7 and 8 summarize the estimation results of (3), the dynamic response of plant-level markdowns for administrative workers and production workers to the 2010 tariff reform.

Similar to the early trade liberalization in the 1980s, the response to the 2010 tariff reforms is substantially different for administrative and production workers. The change in the plant-level markdowns for administrative workers is not significantly associated

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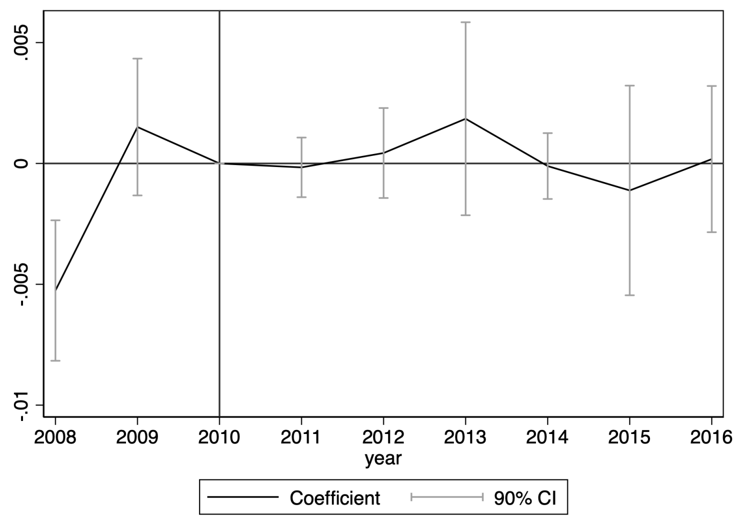
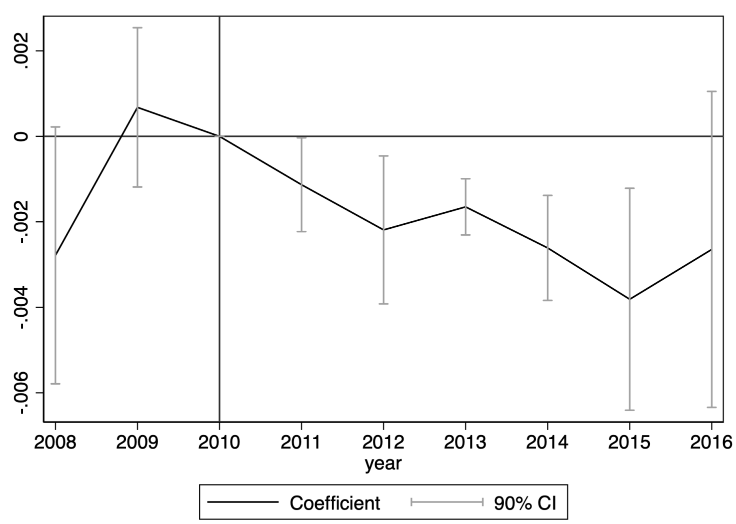
Figure 7: Dynamic response of plant-level markdowns (Administrative worker)



Note: This figure plots the estimated coefficients of a regression equation with 90% confidence intervals. The left-hand side variable is the log difference between markdowns in year t indicated on the horizontal axis and markdowns in 2010. All the regressions include controls for industry-fixed effects, plant employment size, and region-fixed effects.

Figure 8: Dynamic response of plant-level markdowns (Production worker)



Note: This figure plots the estimated coefficients of a regression equation with 90% confidence intervals. The left-hand side variable is the log difference between markdowns in year t indicated on the horizontal axis and markdowns in 2010. All the regressions include controls for industry-fixed effects, plant employment size, and region-fixed effects.

with the tariff reduction in 2010. The estimated coefficients are not statistically significant except for the year 2008 and fluctuate around zero. On the other hand, the effects on markdowns for production workers are statistically significant after the tariff reform

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in 2010, and the statistical insignificance of the coefficients for the years 2008 and 2009 work as the placebo tests.

The results suggest that trade liberalization and import competition affect only the markdowns of unskilled and/or production workers, not those of skilled and/or administrative workers. This finding has an implication for the distributional consequences of trade liberalization. Many researchers find that wage inequality widens after trade liberalization in developing countries. (See Goldberg and Pavcnik (2016) for the summary of the literature.) This is the case for Colombia, too. Attanasio et al. (2004) find an increase in the skill premium after the drastic tariff reduction of the 1980s. However, the previous studies mainly focus on the theoretical implications from the Hecksher-Ohlin type neoclassical model in which the sectoral reallocation and the change in the return to human capital would be the main driver for the increase in the skill premium. The findings in this paper address another mechanism behind the increasing wage inequality after the trade liberalization. The increase in markdowns for unskilled workers combined with no changes in markdowns for skilled workers implies that the wage inequality between skilled and unskilled workers increases due to tariff reduction. [11] Wage inequalities in a perfectly competitive labor market, as in the neoclassical trade model, and inequalities due to markdowns from imperfect labor markets, also have very different policy implications. The first requires compensating workers who are forced to change or lose jobs, whereas the latter also requires addressing the inefficiencies in the labor market and facilitating reducing search costs for workers and/or local labor market concentration.

7 Conclusion

This paper estimates plant-level and aggregate markdowns in the Colombian manufacturing sector, 1977-2020, using the "production approach" with plant-level microdata. Employers exercise a certain degree of labor market power, and it has increased over time. Using large-scale trade liberalization and tariff reforms, we show that the tariff re-

[11] This increase in labor market power is in line with the findings in Felix (2021) for Brazilian trade liberalization.

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duction and increased import competition increased plant-level markdowns. The markdowns are systematically higher for skilled workers than for unskilled workers, but the effect of trade liberalization on markdowns concentrates on unskilled production workers, widening the wage gaps after the trade liberalization.

The paper leaves several important works undone for future research. First and foremost, it is worth building a theoretical model to investigate the mechanism underlying the empirical findings between trade liberalization and increased labor market powers. Search frictions and job differentiation with the oligopsonistic competition are the two main mechanisms widely studied in the macro labor literature. However, our empirical findings of no connection between markdowns and labor market concentration during the trade liberalization contradict with the theoretical model of job differentiation with the oligopsonistic competition. It may explain the finding that markdowns for skilled workers are consistently higher than those for nonskilled production workers because skilled jobs are often more differentiated, and their tasks are less general than manual production tasks. But, the change in markdowns is concentrated on production workers and without a rise in labor market concentration.

On the other hand, in a search model, such as Burdett and Mortensen (1998), workers accept low-wage job offers because they search for and move up to better jobs later. In developing countries, manufacturing sectors tend to be popular among low-skilled workers and thus at higher rungs of the job ladder for them. If manufacturing jobs are at a low rung for skilled workers and at a high rung for nonskilled workers, the markdowns would be higher for skilled workers than for unskilled workers. Trade liberalization might have lowered the relatively high position of production workers' job ladders in the most affected sectors, but not the already low position of nonproduction workers' job ladder, keeping their markdowns unaffected. This is a possible explanation consistent with our empirical findings. In the trade literature, there is little theoretical or quantitative work on labor market power and the consequences of trade liberalization, especially for different skill groups. Extending a macro labor model of labor market monopsony power with search frictions by incorporating international trade and different types of workers

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is a possible next step in this direction so that one can account for our empirical findings, i.e., higher markdowns for high-skilled workers, but higher effects of trade liberalization on markdowns for unskilled workers.

Second, more robustness checks are needed for our empirical analysis. We estimate the effects of tariff reduction on markdowns but not on wages per se. Also, we have not yet fully exploited the spatial nature of the local labor market, that is, the import exposure of the local labor market and its effect on the local aggregate of markdowns, although the information on plant-level location at the local labor market level is required for this purpose.

Third, the improvement on the "production approach" should be made to confirm the robustness of the results. Although the translog production function allows output elasticities to differ flexibly, it allows only Hicks-neutral technological differences across plants and time. Thus, it cannot distinguish changes in the exercise of market power from capital-biased or labor-augmenting productivity differences.[12] Another problem is the existence of multi-product plants and heterogeneous output and input qualities. After trade liberalization, exporters produce higher quality products, and the quality of inputs from foreign countries improves, which affects the estimates of a production function (De Loecker et al. (2016)). With access to the output quantity measure at the plant level, a framework that accounts for both output and input price variation can be used to improve the estimation of plant-level markdowns.[13]

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[12] There is an emerging literature on estimating production functions with labor-augmenting productivity differences, but the existing methodologies (Doraszelski and Jaumandreu (2018), Raval (2022), Demirer (2022))need to assume labor as a flexible input, not subject to market power.

[13] After applying for access and visiting the statistical office in Colombia, we can use such a dataset.

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