Trade Liberalization in Oligopsony*

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Abstract

Trade liberalization in oligopsonistic environments can distort welfare by amplifying firms' labor market power, thereby exacerbating within-firm wage dispersion. We empirically study this distortion using a quasi-experiment provided by Taiwan's Economic Cooperation Framework Agreement (ECFA) with China, which liberalized trade for a selective set of product categories. Focusing on Taiwanese machinery manufacturers, we find that the ECFA increased overall wages by 6% but concurrently raised wage markdowns by 9.4% over low-skilled workers. The resulting heterogeneous markdown response–indicated by unaffected markdowns over skilled workers–aligns with an increase of 7.2% in within-firm wage dispersion.

Keywords: *Trade Liberalization, Labor Market Power, Wage Markdown, Within-Firm Wage Dispersion*

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I Introduction

A substantial body of empirical literature has documented significant deviations of real-world economies from the idealized model of perfect competition in both product and factor markets (Berry, Levinsohn, and Pakes (1995), Nevo (2001), De Loecker and Warzynski (2012), Autor, Dorn, Katz, Patterson, and Van Reenen (2020), De Loecker, Eeckhout, and Unger (2020), Berger, Herkenhoff, and Mongey (2022), Yeh, Macaluso, and Hershbein (2022), Lamadon, Mogstad, and Setzler (2022)). This raises persistent concerns about potential welfare losses resulting from "market power".

The theory of international trade suggests that an open economy can mitigate market inefficiencies caused by market power in product markets (Melitz and Ottaviano (2008), Holmes, Hsu, and Lee (2014), Edmond, Midrigan, and Xu (2015), Arkolakis, Costinot, Donaldson, and Rodríguez-Clare (2019)). This occurs through the reallocation effect of trade (Melitz (2003)): as domestic firms face heightened competition from abroad, less productive producers are driven out of the market, leading to a more efficient allocation of resources among more productive firms. These efficiency gains are commonly referred to as the "pro-competitive gains from trade". However, when firms also exert monopsony power in factor markets, this reallocation may have adverse consequences. In such settings, the concentration of production among fewer top firms can suppress factor payments even further. Thus, trade liberalization has the potential to exacerbate monopsony power, potentially undermining the overall efficiency gains typically associated with open markets.

To investigate this, in this paper, we employ a firm-level dataset from Taiwan that uniquely links firm sales and export data with detailed information on employee composition. This feature enables us to estimate firms' monopsony power in labor markets characterized by heterogeneous skill levels. We then empirically examine whether trade liberalization amplifies monopsony power and whether this amplification varies across labor markets for different skill groups —a mechanism with important implications on wage inequality (Deb et al. (2024)).

To guide the empirical analysis, we first lay out a theoretical conceptual framework with parametric assumptions widely used in the international trade and labor economics literature (Edmond, Midrigan, and Xu (2015), Berger, Herkenhoff, and Mongey (2022), Gutiérrez (2022), Deb, Eeckhout, Patel, and Warren (2024)). The model features two identical countries, each with a continuum of markets. In each country, there exists a representative household that supplies low- and high-skilled labor and consumes differentiated goods produced by firms. The Constant-Elasticity-Of-Substitution (CES) preferences lead to parametric product demand curve and labor supply curves. Each market consists of a finite number of firms that engage in oligopolistic competition on the product side and oligopsonistic competition in the labor markets. Firms operate with a skill-biased technology, which makes high-skilled labor disproportionately more productive at more productive firms. After paying fixed cost of exporting, firms can enter foreign markets and serve foreign household.

In this parametric framework, product markups and labor markdowns increase with a firm's share of sales and employment in the market. Following trade liberalization, resources are reallocated toward more productive exporting firms that can overcome fixed entry costs and expand sales into foreign markets. In contrast, non-exporters experience declining profit margins due to intensified domestic competition. This reallocation of resources contributes to widening between-firm wage inequality. At the same time, concentration of resources increases labor markdowns for exporters while reducing them for non-exporters. However, this rise in labor markdowns among exporters is not uniform across skill levels. Because productivity is skill-biased, high-skilled workers are disproportionately employed by more productive firms, whereas low-skilled workers are more evenly distributed. As a result, the reallocation of labor following trade liberalization is more pronounced for low-skilled workers, leading to a larger increase in their wage markdowns. This, in turn, exacerbates within-firm wage inequality among exporters. This mechanism highlights a novel channel through which heterogeneous changes in labor market power across skill groups can amplify wage inequality.

Guided by the theoretical implications, we conduct empirical analysis. Building on the seminal work of Yeh et al. (2022) and Rubens (2023), our empirical framework assumes that firms internalize finitely elastic labor supply curves and operate in imperfectly competitive labor markets, as outlined in the theoretical model. However now, without imposing any parametric assumptions on the labor supply curves, we identify and estimate wage markdowns at the firm level. The key to this identification is the presence of a flexible input, other than labor, which is free of adjustment costs and does not exhibit monopsony power. The wedge for the flexible input may reflect product markups; however, the ratio of the labor wedge to the wedge for the flexible input accounts for product markups and enables the identification of labor markdowns. These markdowns are expressed through two ratios: the ratio of output elasticities and the relative expenditure ratio between labor and the flexible input. While the latter can be directly measured from the data, the former is a by-product of production function estimation.

Once we estimate firm-level wage markdowns, we examine the effect of trade liberalization on labor monopsony power. For this, we exploit the trade liberalization episode between Taiwan and China: the Economic Cooperation Framework Agreement (ECFA) announced in 2010. The ECFA provides a clean quasi-experiment for our empirical analysis. First, to maintain the competitiveness of Taiwanese manufacturers in the Chinese market following China's signing of the ASEAN-China Free Trade Agreement (CAFTA) with other Asia-Pacific nations, the implementation of the ECFA was expedited. This rapid negotiation process made the trade liberalization largely unanticipated by Taiwanese firms. Second, the liberalization was focused on a selected set of product categories, primarily in the chemical materials, machinery and equipment, and textile sectors. The selection process for these products is arguably free from strategic manipulation by either Taiwan or China, as it was based on the product list negotiated under CAFTA.

We focus on the Machinery and Equipment Industry, one of the sectors most benefited by the ECFA. We specify a flexible translog production function at the firm level, incorporating low-skilled labor (production workers), high-skilled labor (nonproductive workers), materials, and capital. As is standard in the literature, we treat labor and materials as static inputs, while capital is considered a dynamic input. Assuming an AR(1) process for unobserved firm-level productivity, we apply the dynamic panel approach outlined in Blundell and Bond (2000) to estimate the production function. Specifically, we construct a moment condition based on the fact that capital is predetermined, while labor and materials can be freely adjusted and chosen contemporaneously. Consequently, the first differences of the unobserved productivity innovations are uncorrelated with past labor and material choices and the current capital stock. The median firm-level labor markdowns for low-skilled labor and high-skilled labor are estimated to be 1.69 and 1.11, respectively. This demonstrates a significant amount of labor market power over low-skilled labor, with a median worker being compensated by only 59% of the marginal revenue product.

After estimating the firm-level labor markdowns for each type of labor over time, the quasi-experiment created by the ECFA provides a natural setting for a difference-in-differences analysis to estimate the treatment effect of trade liberalization on labor market power. We focus on a sample of 'ECFA exporters'–firms that have consistently exported and have exported ECFA products between 2006 and 2017. Within this group, the treated firms are those that exported to China throughout the sample period, while the control firms are those that exported ECFA products to other countries but not to China. To address the unbalancedness between treated and control groups, we estimate the average treatment effect on treated (ATET) using a doubly-robust difference-in-differences estimator as in SantAnna and Zhao (2020), Callaway and SantAnna (2021), and Caetano and Callaway (2024). We construct the counterfactual potential outcomes by weighting the control groups based on the propensity scores of exporting to China. We further perform a regression adjustment for the outcome variables to avoid the bias resulting from the mis-specification of propensity score models.

Our treatment effect analysis reveals that, on average, exporters affected by the ECFA increase their wage markdowns for low-skilled labor by 9.4% relative to the control group. In contrast, wage markdowns for high-skilled labor remain unchanged, consistent with the comparative statics implied by our theoretical framework. In terms of wage inequality, the average employee at treated exporters receives 6% higher compensation, driven by increased export sales — suggesting a rise in between-firm wage dispersion. However, these workers remain underpaid relative to their marginal product, as evidenced by the increase in average markdowns. To assess within-firm wage dispersion, we examine how labor market power interacts with trade liberalization. We further find that the ECFA led to more dispersed wage distributions within firms: the coefficient of variation in wages among treated exporters is up to 7.2% higher than that of control firms, reflecting the heterogeneous markdown responses predicted by the model.

Our paper connects and contributes to several strands of literature. First, it contributes to works that study the welfare effect of trade liberalization when markets are not perfectly competitive (Melitz and Ottaviano (2008), Edmond, Midrigan, and Xu (2015), Arkolakis, Costinot, Donaldson, and Rodríguez-Clare (2019), MacKenzie (2021), Gutiérrez (2022)). In contrast to existing studies, our methodology estimates empirical markdowns without imposing strong assumptions about the competitive structure of labor markets — assumptions that often necessitate specific parametric distributions of markdowns. Second, our study complements recent empirical literature that studies the causal impact of globalization on empirical labor markdowns. Xie et al. (2024) quantifies the welfare effect associated with labor reallocation after China joined the World Trade Organization (WTA) in 2001. The paper finds that lower input tariffs decrease the variance in labor markdowns, alleviating the misallocation in the labor market. Lu et al. (2019) finds that FDI liberalization widened wage markdowns and decreased labor income share in output value-added following China's regulation changes upon its accession to WTO[1]. Compared to this literature, leveraging the unique features of our dataset, we are able to retrieve markdowns across heterogeneous skill groups and examine whether the disproportionate response of these markdowns to trade liberalization contributes to the widening of wage inequality. Lastly, our paper speaks to the literature that studies the secular rise of labor market power and the emergence of superstar firms (Autor, Dorn, Katz, Patterson, and Van Reenen

[1] In addition, Casacuberta and Gandelman (2023) finds decreasing wage markdowns and increasing firm-level product markups after the establishment of wage councils to handle sector-level, centralized wage negotiations and raise sector-level minimum wages. Mertens (2022) uses German manufacturing firm-product data and finds that rising labor market power explains half of the fall in labor's share in output value-added.

(2020), De Loecker, Eeckhout, and Unger (2020), Berger, Herkenhoff, and Mongey (2022), Deb, Eeckhout, Patel, and Warren (2024)). In our paper, we focus on the response of wage markdowns to trade liberalization episodes in the presence of labor market power.

The remainder of the paper is structured as follows. Section II presents a conceptual framework that illustrates the effect of trade on labor markdowns and within-firm wage dispersion. Section III describes the data and empirical setting, estimates the firm-level labor markdowns, and investigates the causal impact of trade liberalization on labor markdowns and within-firm wage dispersion. Section IV concludes.

II Conceptual Framework

In this section, we propose a simple model to illustrate the core mechanism of the paper, which serves to provide theoretical guidance for our empirical analysis. In the model, trade liberalization facilitates resource reallocation towards productive exporting firms, which widens between-firm wage inequality. The reallocation of employment market share increases wage markdowns of exporters, while decreases those of non-exporters. At the same time, due to skill-biased technology, reallocation effect is disproportionately stronger in the low-skilled labor market. Larger increase in low-skilled wage markdown raises within-firm wage inequality of productive exporters.

II.I An Illustrative Parametric Example

We consider an open economy with two identical countries. In each country, there exists a representative household and heterogeneous firms. The household supplies low- and high-skilled labor in oligopsonistic labor markets and consumes goods produced by firms in oligopolistic product markets. There is a continuum of identical markets with mass I. Each market $i \in I$ accommodates a finite number of firms, indexed by $n \in \{1, 2, ..., N\}$. Each firm hires both skills and produces a differentiated product, taking into account the residual labor supply curves and product demand curve. In what follows, we focus on the Home country, and all the foreign variables will be denoted with a superscript star ($*$).

Preferences. The Home household maximizes the following static utility:

$$\max_{C_{ni},L_{ni},H_{ni}} C - \frac{1}{\overline{\zeta}_L}\frac{L^{1+\zeta_L}}{1+\zeta_L} - \frac{1}{\overline{\zeta}_H}\frac{H^{1+\zeta_H}}{1+\zeta_H},$$

$$s.t. PC = W_L L + W_H H + \Pi,$$

with $\overline{\zeta}_S, \zeta_S > 0, S \in \{H, L\}$. P, W_L, W_H denote the price index of consumption good, and wage indices of low- and high-skill labor. C, H, L are the Constant Elasticity of Substitution (CES) aggregator of consumption, labor supply across firms within markets and across markets. That is,

$$C = \left(\int_{i\in I} I^{-\frac{1}{\theta}} C_i^{\frac{\theta-1}{\theta}} di\right)^{\frac{\theta}{\theta-1}}, C_i = \left(\sum_{n\in N} C_{ni}^{\frac{\gamma-1}{\gamma}} + \sum_{n\in N^*} C_{ni}^{*\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}},$$

$$S = \left(\int_{i\in I} I^{\frac{1}{\theta_S}} S_i^{\frac{\theta_s-1}{\theta_s}} di\right)^{\frac{\theta_s}{\theta_s-1}}, S_i = \left(\sum_{n\in N} S_{ni}^{\frac{\gamma_s-1}{\gamma_s}}\right)^{\frac{\gamma_s}{\gamma_s-1}}.$$

Goods and labor within a market are more substitutable compared to goods and labor across markets, with elasticities $\eta > \theta > 0$ and $\eta_S > \theta_S > 0$. Due to international trade, Home household can also consume the products produced by Foreign firms, C_{ni}^{*} [2].

Household utility maximization leads to the following inverse product demand curve and labor supply curves:

$$C_{ni} = \frac{1}{I} P_{ni}^{-\eta} P_j^{\eta-\theta} P^{\theta} C, C_{ni}^{*} = \frac{1}{I} P_{ni}^{*-\eta} P_j^{\eta-\theta} P^{\theta} C, \tag{1}$$

$$S_{ni} = \frac{1}{I} W_{S,ni}^{\gamma_S} W_{S,i}^{\theta_S-\gamma_S} W_S^{-\theta_S} S, \tag{2}$$

[2] Note that due to fixed cost of exporting, not all the Foreign firms will enter Home market. Hence, $N \neq N^*$. Since we have two identical countries, C_{ni}^* is also the consumption of Foreign household on Home product.

where market price and wage indices are given by

$$P_i = \Big(\sum_{n=1}^{N} P_{ni}^{1-\gamma}\Big)^{\frac{1}{1-\gamma}}, P = \Big(\int_{i\in I} \frac{1}{I} P_i^{1-\theta} di\Big)^{\frac{1}{1-\theta}},$$

$$W_{S,i} = \Big(\sum_{n=1}^{N} W_{s,ni}^{1+\gamma_S}\Big)^{\frac{1}{1+\gamma_S}}, W_S = \Big(\int_{i\in I} \frac{1}{I} W_{S,i}^{1+\theta_S}\Big)^{\frac{1}{1+\theta_S}}.$$

Production. Each firm n in market i produces a differentiated product using the following technology,

$$y_{ni} = \left(\left(z_{L,ni}L_{ni}\right)^{\frac{\sigma-1}{\sigma}} + \left(z_{H,ni}H_{ni}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where $\sigma > 1$ is elasticity of substitution between low- and high-skill labor. $z_{S,ni}$ captures the skill-specific productivity. It's straightforward to incorporate "skill-biased productivity" (Burstein and Vogel (2017)) in our model. To see this, we could specify the skill-specific productivity to be $z_{S,ni} = z_{ni}\Phi_{S,ni}$, where z_{ni} is the Hicks-neural productivity, and the relative productivity of skills $\frac{\Phi_{H,ni}}{\Phi_{L,ni}}$ is increasing in z_{ni}.

Since the economy consists of a continuum of markets, each firm is small relative to the whole economy. However, within each market, there are finite number of firms. Hence, firms engage in oligopsonistic and oligopolistic competition with each factor and product market, and maximize profit taking into the product demand curve and labor supply curves given in Equations (1) and (2). Furthermore, we assume that there exist both (iceberg) trade cost $\tau > 1$ and fixed cost $F_x > 0$ for a firm to serve Foreign household. In order to deliver 1 unit of product, τ units need to be shipped. Part of the trade cost reflects physical shipping cost, while the rest reflects man-made trade policies such as tariff. We assume fixed cost F_x is in the unit of domestic final consumption good C, which serves as the numeraire of the economy.

Formally, firm's profit maximization problem is given by

$$\Pi_{ni} = \max_{H_{ni},L_{ni},q_{ni},q^*_{ni},1_{x,ni}\in\{0,1\}} P_{ni}q_{ni} + 1_{x,ni}P^*_{ni}q^*_{ni} - W_{H,ni}H_{ni} - W_{L,ni}L_{ni} - 1_{x,ni}F_x,$$

$$s.t.(1),(2), q_{ni} + \tau 1_{x,ni} q^*_{ni} = \left(\left(z_{L,ni} L_{ni} \right)^{\frac{\sigma-1}{\sigma}} + \left(z_{H,ni} H_{ni} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where $1_{x,ni} \in \{0,1\}$ indicates firm's decision of whether to export and serve the Foreign country, and q^*_{ni} is the corresponding quantity received by the Foreign household. Optimal decision leads to the following optimal demand of skill S labor,

$$\frac{P_{ni} y_{ni}^{\frac{1}{\sigma}} z_{S,ni}^{\frac{\sigma-1}{\sigma}} S_{ni}^{-\frac{1}{\sigma}}}{\mu_{ni}} = W_{S,ni} \delta_{S,ni}, \tag{3}$$

where marginal revenue product of labor equates marginal cost of labor. Due to market power, firms internalize the effect of their own quantity choices on their prices and wages. This leads to product markup and labor markdown given by μ_{ni} and $\delta_{S,ni}$. They are closely connected to firm's within-market "market share", and are given by

$$\mu_{ni} = \frac{1}{1 - [\frac{1}{\theta} x_{ni} + \frac{1}{\gamma}(1 - x_{ni})]}, \tag{4}$$

$$\delta_{S,ni} = 1 + \frac{1}{\theta_S} e_{S,ni} + \frac{1}{\gamma_S}(1 - e_{S,ni}). \tag{5}$$

x_{ni} denotes firm n's domestic sales share in market i, $x_{ni} = \frac{p_{ni} q_{ni}}{P_i C_i}$, and $e_{S,ni}$ denote firm n's wage bill share of skill S in market i, $e_{S,ni} = \frac{W_{S,ni} S_{ni}}{W_i S_i}$. Given that within-market elasticity is larger, firms with larger product market share and factor market share have larger markups and markdowns. For example, consider a firm with market shares $x_{ni} \approx 1, e_{S,ni} \approx 1$. Such firm has the largest markup $\frac{\theta}{\theta-1}$ and markdown $1 + \frac{1}{\theta_S}$. Since the firm controls the whole market, its markup and markdown are only related to across-market substitution.

If firm chooses to serve Foreign country, optimal quantity q^*_{ni} must be such that

$$\frac{P_{ni}}{\mu_{ni}} = \frac{1}{\tau} \frac{P^*_{ni}}{\mu^*_{ni}}. \tag{6}$$

where μ^*_{ni} denotes firm's markup in the Foreign market[3] The intuition of Equation (6) is that firm allocates quantities in Home and Foreign markets such that marginal

[3]That is, $\mu^*_{ni} = \frac{1}{1 - [\frac{1}{\theta} x^*_{ni} + \frac{1}{\gamma}(1 - x^*_{ni})]}$ and $x^*_{ni} = \frac{p^*_{ni} q^*_{ni}}{P_i C_i}$.

revenue product of labor are equalized[4]. Firm will choose to export if under this optimal quantity q_{ni}^*, the net profit of serving Foreign country is larger than the fixed cost of exporting F_X.

Finally, implied by Equation (3), within-firm wage inequality satisfies:

$$\ln(\frac{W_{H,ni}}{W_{L,ni}}) = \ln(\frac{\delta_{L,ni}}{\delta_{H,ni}}) + \frac{\sigma-1}{\sigma}\ln(\frac{z_{H,ni}}{z_{L,ni}}) - \frac{1}{\sigma}\ln(\frac{H_{ni}}{L_{ni}}). \tag{7}$$

It depends on the relative productivity of skills, as well as the wage markdowns in our oligopsonistic setup. If, for example, low-skilled labor exhibits larger wage markdown, this increases the within-firm wage inequality.

Equilibrium. The equilibrium of the economy can be defined in terms of allocations q_{ni}, q_{ni}^*, S_{ni} and prices $P_{ni}, W_{S,ni}$ such that they satisfy household's and firms' first-order conditions, and all the markets clear.

II.II The Effect of Trade Liberalization

When markets undergo trade liberalization with lower tariff (smaller trade cost τ), focusing on the Home country, there are two major effects. First, within each Home market, there will be entry of foreign products, which intensifies the product market competition. Second, Home firms have the potential to access Foreign household and gain exporting profits. Due to fixed cost of exporting, these effects generates *selection* of firms (Melitz (2003)) and resource reallocation. Productive firms manage to overcome the fixed cost and become exporters. This expands their production scales and profits. On the other hand, unproductive firms only serve domestic markets, and their profit margins decline due to foreign product competition.

Resource reallocation has salient implications on wage markdown and within-firm wage inequality implied by Equation (7). After trade liberalization, exporters exhibit even larger factor market shares and exert larger wage markdowns, while wage markdowns of non-exporters decline. However, the magnitude of the exporter markdown

[4]Notice that without endogenous markup, $P_{ni}^* = \tau P_{ni}$ as in a monopolistic competition environment such as Melitz (2003).

increase can be different for different skills. This is due to the fact that reallocation effect can be much stronger for one skill, compared to the other. For example, as one can expect, due to skill-biased productivity, high-skilled labor are hired much intensively by productive firms. Because of this, factor market shares across firms in the high-skilled labor market are already concentrated among the top, compared to the low-skilled labor market. Therefore, after trade liberalization, further reallocation of factors will be disproportionally stronger in the low-skilled labor market. This results in larger increase in wage markdown for low-skilled labor, which ultimately raises the within-firm wage inequality for exporters after trade liberalization. We view this as a new mechanism that trade liberalization can lead to higher within-firm wage inequality for exporters, compared to non-exporters[5].

To illustrate the mechanism qualitatively, we construct the following numerical example. We consider a continuum of markets with mass one ($I = 1$). In each market, there are two firms ($N = 2$) competing with each other in an oligopolistic fashion in both product and labor markets. Firm's production technology exhibits skill-biasedness. Without loss of generality, we assume that firm 2 is more productive, and demands disproportionately more high-skilled labor. We select productivities such that in the high-tariff trade equilibrium, firm 2 employs 95% of high-skilled labor within a market, while only 65% of low-skilled labor. We posit that products and labor are more substitutable within the sector. Specifically, we set $\eta = 6, \theta = 1.2$, $\eta_S = 2$, $\theta_S = 0.8$. We specify fixed cost F_x such that only firm 2 is willing to serve Foreign market. We first solve the high-tariff trade equilibrium. We then decrease the tariff to reflect trade liberalization, and re-solve the low-tariff trade equilibrium.

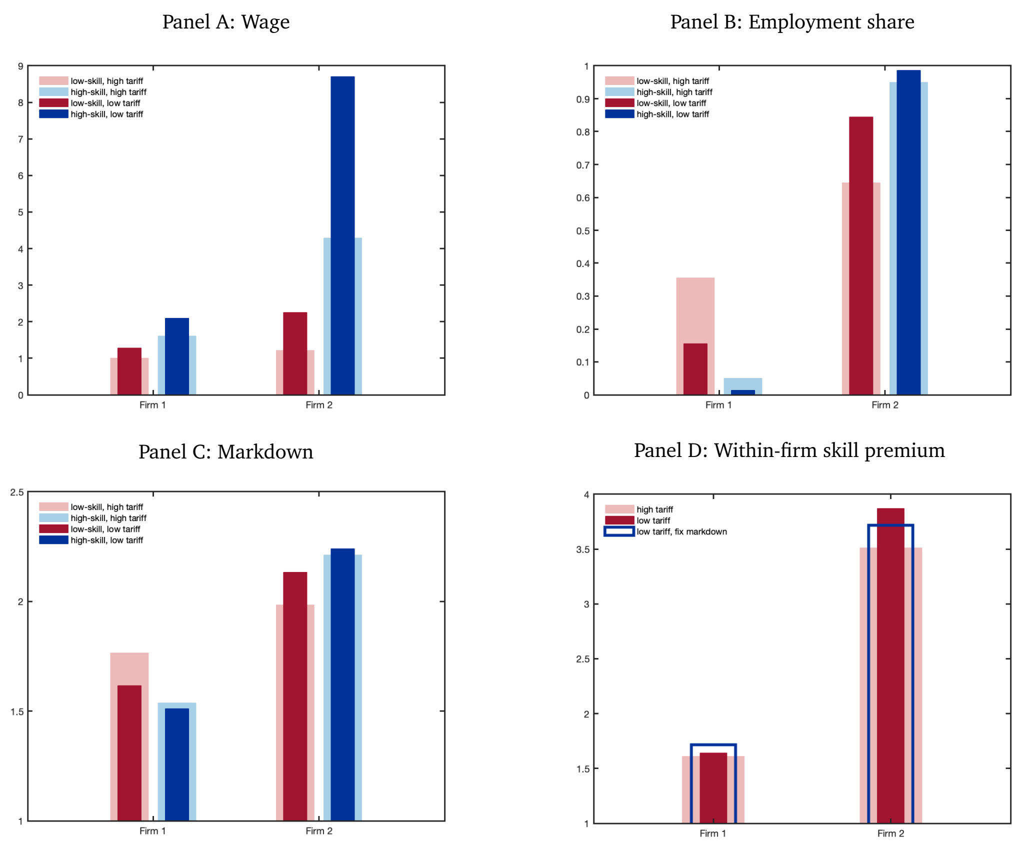
Panel A of Figure 1 illustrates the effect of trade liberalization on wages[6]. We observe that under skill-biased productivity, firm 2 offer disproportionately higher wages to high-skilled labor. This becomes increasingly so after trade liberalization as firm 2 further expands the production scale. Panel B shows that there exist resource reallocation towards firm 2 after trade liberalization. However, the effect in the low-skilled

[5]Under skill-biased productivity, resource reallocation also increase the relative aggregate demand of high-skilled labor. This increases the within-firm wage inequality across all the firms.

[6]Firm 1's low-skilled wage in the high-tariff equilibrium is normalized to 1.

labor market is much stronger. The reallocation of factor market share leads to the changes in wage markdowns. From Panel C, we observe that markdowns of both skills increase for firm 2, and decrease for firm 1. At the same time, the increase in low-skilled markdown is disproportionately larger. Finally, Panel D illustrates the change in within-firm wage inequality. Within-firm wage inequality increases in both firms due to rising aggregate demand of high-skilled labor in the economy; nevertheless, the increase is stronger within firm 2. To isolate the role of wage markdowns. we further show the hypothetical within-firm wage inequality fixing the wage markdowns at the high-tariff equilibrium level. After doing so, we observe that the increase in wage inequality within firm 2 drops significantly. This highlights that the new mechanism we propose is qualitatively important.

Figure 1: A Qualitative Example: The Effect of Trade Liberalization



Note: The figure displays the effect of trade liberalization on wage, employment share, wage markdown and within-firm skill premium. Firms are ranked according to their productivity level. The baseline equilibrium involve high tariff. The trade liberalization equilibrium refers to the one with low tariff.

III Empirical Application

III.I Institutional Backgrounds

Our empirical application focuses on the impact if the Economic Cooperation Framework Agreement (ECFA) on the labor market power of Taiwanese machinery and equipment manufacturing firms from 2006 to 2017. Below, we provide an overview of the ECFA and the Taiwanese machinery and equipment sector.

Economic Cooperation Framework Agreement

Following accession to the World Trade Organization (WTO) in 2001, China emerged as an important market for global manufacturers.[7] The increasing prominence of Chinese final goods manufacturers prompted the development of regional trade agreements (RTAs) to strengthen trade relations with China. Key agreements include the ASEAN-China Free Trade Agreement (CAFTA), implemented in January 2010, and the Regional Comprehensive Economic Partnership (RCEP), which began formal negotiations in 2011.

The establishment of CAFTA posed significant competitive challenges for Taiwanese manufacturers in the Chinese market, as Taiwan lacked preferential tariff agreements with China. To address this, the Taiwanese government initiated negotiations for a bilateral trade agreement with China in 2010. This effort culminated in the signing of the Economic Cooperation Framework Agreement (ECFA) in September 2010, following rapid negotiations that began earlier that year.

To mitigate potential political and economic concerns associated with rapid trade liberalization, the ECFA included an initial phase of tariff reductions targeting a limited set of products (referred to as Early Harvest Products) prior to broader liberalization. However, the progress of the agreement was interrupted in 2014 due to Taiwan's Sunflower Movement, resulting in the continued liberalization of only early harvest products.[8]

[7] This subsection draws from Hong and Yang (2011) and Chou (2009).

[8] See Michael Turton, "The economic legacy of Taiwans Sunflower movement," *Taipei Times*, March 28, 2022; James X. Morris, "Brian Hioe: The Sunflower Movement, 4 Years Later," *The Diplomat*, July

The Early Harvest Product list consisted of 539 Taiwanese exports to China and 267 Chinese exports to Taiwan. Notably, the selection of Taiwanese exports receiving preferential tariff reductions mirrored the liberalized product list under CAFTA, thereby restoring the competitiveness of Taiwanese goods in the Chinese market vis-à-vis ASEAN exporters. The agreement significantly boosted Taiwan's aggregate exports to China, which increased by 35% within the first three years of implementation. In contrast, Taiwans import volume from China remained relatively unchanged during the same period.

Overall, the ECFA event provides a unique quasi-experimental setting for economic analysis. First, the agreement's rapid negotiation and implementation rendered its announcement unanticipated by Taiwanese firms. Second, the selective liberalization of specific products allows for a clear division of firms into treated and control groups within narrowly defined industries. Finally, the alignment of the product selection process with the CAFTA liberalized product list minimized the potential for strategic manipulation by either Taiwan or China.

Taiwanese Machinery and Equipment Industry

Among the 539 Early Harvest Products from Taiwan to China, the largest categories were chemical materials (88 items), machinery and equipment (107 items), and textiles (137 items). We aim to focus on machinery and equipment manufacturers.

The choice of this industry is motivated by its significant benefit from the ECFA. Even prior to the agreement, China was Taiwan's largest export market for machine tools, highlighting the critical role of tariff reductions for this sector. Following the implementation of the ECFA, the machinery and equipment industry experienced a dramatic 603.5% increase in total export sales to China over a decade.[9]

Additionally, machinery and equipment manufacturers serve a broad range of other manufacturing sectors due to the nature of their products. In contrast, chemical materials and textiles primarily cater to specific downstream industries, such as the paint

18, 2018.

[9] According to the Ministry of Economic Affairs, Taiwan, machinery and equipment exports to China rose from USD 1.1 billion in 2009 to USD 6.9 billion in 2019.

and apparel/footwear sectors. This unique characteristic enables us to isolate the impact of export tariff liberalization on the industry without concerns about confounding effects from complex global supply chain networks.

III.II Data

We use a comprehensive and unique dataset from the Fiscal Information Agency, Ministry of Finance, Taiwan. This dataset integrates multiple rich sources of information, including (1) business tax filings, (2) individual tax filings, and (3) trade custom records. Covering the universe of profit-seeking firms in Taiwan from 2006 to 2017, along with their international transaction records, this dataset offers an unparalleled opportunity to examine the dynamics of a firm's labor market power in response to trade liberalization.

Business tax returns include balance sheets with unique business identification numbers common across years and filing forms. From these sources, we construct a complete panel of firms with the information on their receipts, material input expenditures, and fixed assets (i.e., plant, property, and equipment; PP&E), which are necessary to estimate the production function. The module records the total payroll allocated to production workers for manufacturing processes. We use this variable to measure unskilled labor input as it can account for the quality of production workers. Additionally, the business tax filings provide 6-digit industry codes, allowing us to classify a firm's operating industry based on the first two digits of their code.

The individual earnings data provide details on compensation received from business entities, including salaries and stock-option bonuses. Using unique business identification numbers, we construct firm-level metrics such as the number of employees and total salary payrolls from the business tax return data. We measure skilled labor by calculating total payrolls for non-production workers (e.g., salespersons and executives), obtained by subtracting payrolls for production workers from total salary payrolls. We also use the data to measure a firms payroll structure during a given period, including average employee wage rates and wage dispersion.

The trade customs records encompass all international transactions from Taiwan at the HS six-digit code, firm, destination, and year level. This transaction-level panel enables us to identify (1) exporters of ECFA-liberalized products and (2) whether these firms exported such products to China, allowing us to construct a sample of Taiwanese firms directly exposed to the ECFA (i.e., treated firms).

Sample Construction

Our sample construction procedure begins by cleaning business tax returns and retaining only firms that report positive values for net receipts, material expenditures, property, plant, and equipment (PP&E). These criteria ensure the dataset focuses on economically active firms engaged in meaningful operations. Individual tax records are filtered to include only those with annual earnings exceeding the Taiwanese minimum wage. In keeping with the literature (Lamadon et al. (2022)), we define the primary employer for these workers as the business identification number responsible for the highest salary payrolls. We aggregate the trade custom records to the firm-year level with separate values for total export revenue, China export revenue, ECFA export revenue, and ECFA-China export revenue.

Sales revenue, salary payrolls, and material expenditures are deflated using the GDP deflator, while PP&E is deflated using the investment deflator. We focus on firm-year observations consistently reported across all dataset modules from 2006 to 2017, resulting in an unbalanced panel of 77,667 firm-year observations. Firms with deflated sales revenue below 5 million NTD and fewer than five employees are excluded. Following Ruhl and Willis (2017), we also remove outlier firms with extreme changes in labor employment and sales revenue. After these filters, the dataset includes 41,959 firm-year observations. For production function estimation, we further refine the sample by trimming the 2nd and 98th percentiles based on revenue-to-variable cost ratios, material shares, and labor-to-material expenditure ratios. This trimming yields an estimation sample of 38,610 firm-year observations.

Table 1 describes the variables of interest in our sample. The sample reveals that the size variables of firms–sales, employees, material expenditures, PP&E, direct labor cost–are highly left-skewed, echoing the stylized facts that have been well demonstrated.

Table 1: Sample Description:
Machinery Industry (Observations = 41,959)

	Median	Mean	Std. Dev
Number of employees	14	32.8636	86.0184
Payroll to Non-production worker*	1.5176	7.1624	24.7095
Payroll to Production worker*	3.0155	7.8408	30.6519
Average worker payroll*	0.3365	0.3604	0.1392
Material expenditures*	18.5015	68.2930	213.7901
Plant, Property, and Equipment*	12.1704	51.1191	258.5670
Sales Revenue*	37.5907	138.8340	491.0261

Notes: The table displays the pooled sample averages of the key variables of interest. Variables marked with an asterisk (*) are expressed in deflated millions of 2008 New Taiwan Dollar.

First Glance at ECFA

Table 2 presents a summary of trade activities for Taiwanese machinery firms before and after the implementation of the ECFA. The agreement had a notable impact on both the extensive and intensive margins of exporting ECFA items to China. On the extensive margin, the fraction of firms exporting ECFA items to China increased by 4.7 percentage points following the ECFA. On the intensive margin, the average share of export sales of ECFA items to China, relative to total exports to China, rose by 6.68 percentage points. Similarly, the share of ECFA items in total firm-level export sales increased by 1.14 percentage points. These increases were not driven by declining export sales of non-ECFA items but rather by substantial growth in ECFA-China export revenues. Specifically, the average revenue from ECFA items exported to China grew from 20 million NTD to 34 million NTD, indicating that benefiting firms experienced overall growth in their export performance.

The ECFA also influenced the extensive margins of broader export participation. The fraction of firms exporting ECFA items to any destination rose by 2.86 percentage points, while the fraction of firms exporting to China increased by 1.42 percentage points. Notably, the ECFA encouraged greater participation in the Chinese market, as evidenced by the increase in the share of firms exporting to China. However, the total fraction of exporters remained effectively unchanged, suggesting that the ECFA primarily reallocated existing export activities rather than creating new exporters.

Table 2: Trade before and after ECFA:
Machinery Industry (Observations = 41,959)

	Pre-ECFA	Post-ECFA
Firm-level ECFA-China Export Revenue*	19.9881	34.2688
Firm-level ECFA Item Share of Exports to China	0.5192	0.5860
Firm-level ECFA-China Export Share	0.4312	0.4419
Fraction of Firms Exporting ECFA Items to China	0.2824	0.3294
Fraction of Firms Exporting to China	0.4389	0.4531
Fraction of Firms Exporting ECFA Items	0.5410	0.5696
Fraction of Exporters	0.6639	0.6662

Notes: The table displays the pooled sample averages of the key variables of interest. Revenues are expressed in deflated millions of 2008 New Taiwan Dollar.

* Computed conditional on ECFA-China participation.

The observed improvements in export performance, particularly among firms exporting ECFA items to China, motivate further investigation into how trade liberalization under the ECFA impacted labor market outcomes. To this end, we employ a structural model of firm production to estimate firm-level wage markdowns, which measure the degree of labor market power exerted by firms. By comparing the evolution of wage markdowns for ECFA-China exporters and non-exporters, we aim to assess the labor market power effects of this trade liberalization event. Specifically, we examine whether the increased export revenues associated with the ECFA translated into changes in firms ability to influence wages, thereby shedding light on the broader implications of trade liberalization for labor markets.

III.III Identification of Markdown and Productivity

We identify wage markdowns at the firm level using an empirical model of firm production in the spirit of Dobbelaere and Mairesse (2013), Yeh et al. (2022) and Rubens (2023). The estimation of the model relies on the minimal assumptions that the firm internalizes finitely elastic labor supply and engages in standard optimization processes: profit maximization and cost minimization.

Production

In period t, Taiwanese machinery manufacturer j produces Y_{jt} units of product using four production factors: low-skilled labor L_{jt}, high-skilled labor H_{jt}, raw material M_{jt}, and fixed physical capital K_{jt}. Firms in a given sector are assumed to face a common technological constraint, characterized by a continuously differentiable production function in all four production factors:

$$Y_{jt} = F_{jt}(L_{jt}, H_{jt}, M_{jt}, K_{jt}), \tag{8}$$

which can exhibit flexible output elasticities across firms and times. We denote the output elasticity of low-skilled labor, high-skilled labor, and material input by θ^L_{jt}, θ^H_{jt}, and θ^M_{jt}:

$$\theta^L_{jt} = \frac{\partial F(\cdot)}{\partial L_{jt}} \frac{L_{jt}}{Q_{jt}}; \quad \theta^H_{jt} = \frac{\partial F(\cdot)}{\partial H_{jt}} \frac{H_{jt}}{Y_{jt}}; \quad \theta^M_{jt} = \frac{\partial F(\cdot)}{\partial M_{jt}} \frac{M_{jt}}{Y_{jt}}. \tag{9}$$

Input Markets and Wage Markdowns

We assume low-skilled labor L_{jt}, high-skilled labor H_{jt}, and raw material M_{jt} are static inputs. Let W^L_{jt}, W^H_{jt}, and W^M_{jt} be wage rates for low-skilled, wage rates for high-skilled, and material prices, respectively. We assume that manufacturer j faces a finitely elastic labor supply curve, whose elasticity is denoted by ψ^X_{jt}, $X \in \{L, H\}$:

$$\psi^X_{jt} = \frac{\partial X_{jt}}{\partial W^X_{jt}} \frac{W^X_{jt}}{X_{jt}} > 0. \tag{10}$$

In contrast, all the manufacturers take the price of raw material as given, implying

$$\psi_{jt}^{M} = \frac{\partial M_{jt}}{\partial W_{jt}^{M}} \frac{W_{jt}^{M}}{M_{jt}} = 0. \tag{11}$$

Under the standard profit maximization assumption, manufacturer j's wage markdowns δ_{jt}^{L} and δ_{jt}^{H} depend on the inverse of the perceived elasticity of labor:

$$\frac{MPRL_{jt}^{X}}{W_{jt}^{X}} = \delta_{jt}^{X} = 1 + \frac{1}{\psi_{jt}^{X}}, \tag{12}$$

where $MPRL_{jt}^{X}$ is marginal revenue product of labor type $X \in \{L, H\}$ for manufacturer j.

Behavioral Assumption

Manufacturer j chooses its optimal low-skilled labor, high-skilled labor, and raw material by engaging in short-run cost minimization.

$$\min_{L_{jt}, H_{jt}, M_{jt}} W_{jt}^{L} L_{jt} + W_{jt}^{H} H_{jt} + W_{jt}^{M} M_{jt} \quad \text{s.t.} \quad F_{jt}(L_{jt}, H_{jt}, M_{jt}, K_{jt}) \geq Y_{jt}. \tag{13}$$

With some rearrangements of the terms, the first-order conditions for the cost minimization with respect to labor and raw material can be given by:

$$W_{jt}^{L} + \frac{\partial W_{jt}^{L}}{\partial L_{jt}} L_{jt} = \frac{\lambda_{jt}}{P_{jt}} \theta_{jt}^{L} \frac{R_{jt}}{L_{jt}}, \tag{14}$$

$$W_{jt}^{H} + \frac{\partial W_{jt}^{H}}{\partial H_{jt}} H_{jt} = \frac{\lambda_{jt}}{P_{jt}} \theta_{jt}^{H} \frac{R_{jt}}{H_{jt}}, \tag{15}$$

$$W_{jt}^{M} = \frac{\lambda_{jt}}{P_{jt}} \theta_{jt}^{M} \frac{R_{jt}}{M_{jt}}, \tag{16}$$

where λ_{jt} is the Lagrangian multiplier associated with cost minimization problem (13), and R_{jt} and P_{jt} are firm-level revenues and output prices. Combining equations

(14), (15), and (16) and rearranging the terms, we obtain

$$1+\underbrace{\frac{\partial W_{jt}^{L}}{\partial L_{jt}}\frac{L_{jt}}{W_{jt}^{L}}}_{=\frac{1}{\psi_{jt}^{L}}}=\frac{\theta_{jt}^{L}}{\theta_{jt}^{M}}\frac{W_{jt}^{M}M_{jt}}{W_{jt}^{L}L_{jt}} \tag{17}$$

$$1+\underbrace{\frac{\partial W_{jt}^{H}}{\partial H_{jt}}\frac{H_{jt}}{W_{jt}^{H}}}_{=\frac{1}{\psi_{jt}^{L}}}=\frac{\theta_{jt}^{H}}{\theta_{jt}^{M}}\frac{W_{jt}^{M}M_{jt}}{W_{jt}^{H}H_{jt}} \tag{18}$$

Due to the duality between profit maximization and cost minimization problems, the left-hand sides of equations (17) and (18) represent wage markdowns over low-skilled and high-skilled workers, respectively as (12). We thus identify firm-level wage markdowns using equations (17) and (18), which requires estimation of the production function to identify θ_{jt}^{L}, θ_{jt}^{H}, and θ_{jt}^{M}.

III.IV Estimation of Markdown and Productivity

Estimation Overview

We consider a translog specification for production technology (8):

$$y_{jt}=\underbrace{\beta_l l_{jt}+\beta_h h_{jt}+\beta_m m_{jt}+\beta_k k_{jt}+\sum_{\{n,o\}\in\{l,h,m,k\}}\sum n_{jt}o_{jt}}_{\equiv\mathcal{X}_{jt}'\beta}+\omega_{jt}+\varepsilon_{jt}, \tag{19}$$

where lowercase letters denote the logarithms of variables. We assume ω_{jt} consists of fixed TFP $\omega_j^\star$ and time-varying productivity term $\tilde{\omega}_{jt}$, and $\tilde{\omega}_{jt}$ evolves according to the AR(1) process:

$$\begin{aligned}\omega_{jt}&=\omega_j^\star+\tilde{\omega}_{jt},\\ \tilde{\omega}_{jt}&=\rho\tilde{\omega}_{jt-1}+\xi_{jt},\end{aligned} \tag{20}$$

where ξ_{jt} is idiosyncratic productivity shocks observed to firm j but unobserved to the econometrician. ε_{jt} is the output measurement errors.

The ordinary least squares (OLS) estimator of equation (19) suffers from simultaneity bias due to the endogenous relationship between static production factors (l_{jt}, m_{jt}) and productivity ω_{jt}. Widely adopted approaches to address this issue, often referred to as "control function" methods, are introduced and further developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). These methods rely on either implicit or explicit assumptions of market conduct and adopt the scalar unobservable assumption (i.e., productivity is the sole unobservable factor) to simplify estimation (Doraszelski and Jaumandreu (2019)). However, such methods are incompatible with our oligopolistic and oligopsonistic framework, which incorporates multiple unobservables: productivity, price markups, and wage markdowns.

To address these challenges, we build upon the "dynamic panel" approach proposed by Blundell and Bond (2000), which requires only the standard timeline assumption of input choices and an AR(1) process for logged productivity. In our application, we assume that Taiwanese manufacturer j chooses its capital k_{jt} before observing productivity shock ξ_{jt}, while choosing static production factors (l_{jt}, m_{jt}) after observing ξ_{jt}. This information assumption is widely adopted in previous empirical studies on firm productivity. In addition, we consider a stationary economy in which the underlying primitives of the economy, such as demand, production technology, and investment cost structure, are time-invariant.

To exploit the imposed assumptions, we first quasi-difference production function (19) by using the Markovian structure of productivity in equation (20):

$$\underbrace{\xi_{jt} + (1-\rho)\omega_j^\star + \varepsilon_{jt} - \rho\varepsilon_{jt-1}}_{\zeta_{jt}(\beta,\rho)} = y_{jt} - \rho y_{jt-1} - (\mathscr{X}_{jt} - \rho\mathscr{X}_{jt-1})'\boldsymbol{\beta}. \tag{21}$$

We then difference out $\omega_j^\star$ by within-firm first differencing equation (21):

$$\underbrace{\xi_{jt} - \xi_{jt-1} + \varepsilon_{jt} - (1-\rho)\varepsilon_{jt-1} + \rho\varepsilon_{jt-2}}_{\Delta\zeta_{jt}(\beta,\rho)} = \Delta y_{jt} - \rho\Delta y_{jt-1} - (\Delta\mathscr{X}_{jt} - \rho\Delta\mathscr{X}_{jt-1})'\boldsymbol{\beta}. \tag{22}$$

We perform the method of generalized moments (GMM) to estimate $(\boldsymbol{\beta}, \rho)$ by constructing the moment condition based on the information and stationary assumptions. First, we break down the production function variables into static and fixed parts:

$$\mathscr{X}_{jt}^{v} = (l_{jt}, l_{jt}^{2}, h_{jt}, h_{jt}^{2}, m_{jt}, m_{jt}^{2}, l_{jt}m_{jt}, l_{jt}h_{jt}, h_{jt}m_{jt}),$$
$$\mathscr{X}_{jt}^{f} = (k_{jt}, k_{jt}^{2}, l_{jt-1}k_{jt}, h_{jt-1}k_{jt}, m_{jt-1}k_{jt}).$$

The information assumption implies that the current productivity shock is uncorrelated with all the past labor and material flows and all the current and past capital stocks. Thus, the moment condition is given by

$$\mathbb{E}\Big[\Delta\zeta_{jt}(\boldsymbol{\beta}, \rho) \mid \{\mathscr{X}_{jt-b-1}^{v}, \mathscr{X}_{jt-b}^{f}\}_{b\geq 2}\Big] = 0, \quad \forall t = 4, 5, \ldots, T. \tag{23}$$

Due to the stationary assumption, the parameters of conditional factor demand functions for labor and material and the investment policy function are time-invariant. Hence, within-firm first differences in input factors are not correlated to fixed TFP $\omega_{j}^{\star}$. The moment condition is

$$\mathbb{E}\Big[\zeta_{jt}(\boldsymbol{\beta}, \rho) \mid \{\Delta\mathscr{X}_{jt-b-1}^{v}, \Delta\mathscr{X}_{jt-b}^{f}\}_{b=1}\Big] = 0, \quad \forall t = 3, 4, \ldots, T. \tag{24}$$

We search for $(\rho, \boldsymbol{\beta})$ that best rationalizes the system of moments conditions (23) and (24) via the two-step GMM technique.

Discussion on Production Function

Use of Deflated Revenues as Output - It is well established that using revenues as a proxy for output can lead to the underidentification of markups (Bond et al. (2021)). Bond et al. (2021) argue that when revenue is used instead of true output, the estimated production elasticities correspond to revenue elasticities–i.e., the product of price markups and true output elasticities–leading to biased elasticity estimates and uninformative markups. Given that our analysis employs deflated revenues as a measure of output, a similar identification concern may arise regarding our wage markdown estimates.

However, Yeh et al. (2022) demonstrate that the wage markdown equations (17) and (18) are not subject to this bias. Since the bias affects both the revenue elasticities of labor and materials symmetrically, it cancels out in the markdown equation, which is based on their ratio. Even when the bias asymmetrically affects the revenue elasticities, equations (17) and (18) can be interpreted as identifying wage markdowns relative to those for material input markdowns (Treuren (2023)). Specifically, let $\tilde{\theta}^V_{jt}$ denote the revenue elasticity of input V. Treuren (2023) shows that $\tilde{\theta}^L_{jt}\frac{R_{jt}}{W^L_{jt}L_{jt}}$ and $\tilde{\theta}^M_{jt}\frac{Rjt}{W^M_{jt}M_{jt}}$ represent the wage and material input markdowns, respectively. Thus, equations (17) and (18) capture wage markdowns relative to material input markdowns when revenue is used as the output measure. Overall, our estimates provide a lower bound on wage markdowns and the ECFAs impact on them.

Translog Production Function - In our empirical application, we employ a translog production function specification, which allows us to capture the heterogeneous output elasticities of skilled and unskilled labor. In doing so, we partly accommodate skill-biased technical changes, one of the key dynamics within our conceptual framework.

However, as pointed out by Raval (2023), the translog specification cannot fully capture differences in skill-biased technical changes across firms, particularly their stochastic components. Alternative specifications incorporating stochastic skill-biased technical changes (e.g., Doraszelski and Jaumandreu (2018)) do not facilitate the joint identification of wage markdowns. This is because the identification of both skill-biased technical changes and markdowns relies on variations in the ratio of labor costs to material costs (Rubens et al. (2024)).

To extend our empirical strategy, our immediate goal is to estimate heterogeneous production function parameters across firms based on their importation of capital goods.[10] This approach enables us to recover wage markdowns for skilled and unskilled labor without imposing restrictive labor market conduct assumptions while employing a richer specification that effectively captures stochastic skill-biased technical changes.[11].

[10]Indeed, Rubens et al. (2024) highlights the rise in capital imports attributed to improvements in labor-augmenting productivity in China's non-ferrous metal industry.

[11]This approach aligns with studies on the labor-biased productivity effects of new technology adoption (Foster et al. (2022); Kusaka et al. (2022); Miller et al. (2023))

Estimation Results

Table 3 presents the structural estimates of the translog production function for the machinery equipment industry. Our results demonstrate a degree of persistence in productivity evolution (0.419).

Table 3: Production Function Estimates:
Machinery Equipment Industry

	OLS		GMM	
	Estimate	S.E.	Estimate	S.E.
ρ			0.4189	0.0287
β_l	0.1972	0.0039	0.2022	0.0093
β_{ll}	0.0580	0.0032	0.0525	0.0082
β_h	0.0771	0.0031	0.0648	0.0064
β_{hh}	0.0157	0.0011	0.0132	0.0025
β_m	0.6603	0.0300	0.6534	0.0079
β_{mm}	0.0750	0.0023	0.0633	0.0053
β_k	0.0534	0.0024	0.0736	0.0049
β_{kk}	0.0111	0.0011	0.0090	0.0027
β_{lh}	0.0012	0.0035	0.0057	0.0085
β_{lm}	-0.1060	0.0051	-0.0894	0.0110
β_{lk}	0.0023	0.0027	0.0068	0.0081
β_{hm}	-0.0211	0.0028	-0.0281	0.0067
β_{hk}	0.0034	0.0018	-0.0025	0.0039
β_{mk}	-0.0288	0.0022	-0.0236	0.0048
N	38,610		29,697	

Notes: This table reports the estimates of the production function parameters. All the specifications control for the time fixed effects. Standard errors in parenthesis are clustered at the firm-level.

The corresponding output elasticities of low-skilled labor, high-skilled labor, materials, and capital are summarized in Table 4. The output elasticities of low-skilled labor (θ^L_{jt}), high-skilled labor (θ^H_{jt}), materials (θ^M_{jt}), and capital (θ^K_{jt}) reveal the relative importance of each input in production. Low-skilled labor and materials constitute the bulk of the production process (0.2045 and 0.6531, respectively), while high-skilled labor and capital's contribution is relatively minor, as indicated by its small elasticity values.

Table 4: Wage Markdowns and Output Elasticity:
Machinery Equipment Industry

	Median	Mean	Std. Dev
	Output Elasticity: GMM		
θ^L_{jt}	0.2045	0.2083	0.0891
θ^H_{jt}	0.0682	0.0681	0.0681
θ^M_{jt}	0.6531	0.6448	0.1147
θ^K_{jt}	0.0735	0.0737	0.0070
	Output Elasticity: OLS		
θ^L_{jt}	0.1943	0.1998	0.0951
θ^H_{jt}	0.0915	0.0926	0.0346
θ^M_{jt}	0.6640	0.6543	0.1304
θ^K_{jt}	0.0466	0.0466	0.0357
	Wage Markdowns		
δ^L_{jt}	1.6940	1.8385	1.0563
δ^H_{jt}	1.1069	1.1601	2.6037
N	39,487		

Notes: The table displays the summary statistics for estimated wage markdowns and the output elasticities of labor, material, and capital.

Addressing endogeneity in input choices is crucial in correctly measuring wage markdowns. Compared to ordinary least squares (OLS), our GMM estimates produce larger low-skilled labor output elasticity and smaller material output elasticity, suggesting a potential correction of downward biases in wage markdowns over low-skilled labor based on the OLS-based output elasticities.

The wage markdown estimates highlight the considerable firm's labor market power over low-skilled labor within the Taiwanese machinery industry. The median wage markdown is estimated at 1.694, indicating that the median low-skilled labor in the machinery equipment industry is paid only 59% of their marginal revenue product. In contrast, the median high-skilled labor is paid around 90% of their marginal revenue product–indicated by the median markdown of 1.1069. These different levels of wage suppression align with the global benchmarks. For instance, the median wage markdowns for production and nonproduction workers in the U.S non-electornic machinery sector are 4.530 and 1.359, respectively (Yeh et al. (2022)).

III.V Liberalization Treatment Effects

Sample for Treatment Effect Analysis

The ECFA, in conjunction with the firm-product-level matched panel, allows us to estimate its effects on markdowns and productivity via a difference-in-differences framework. Despite reasonable quasi-experimental variation, a simple comparison of ECFA-target exporters and others post-ECFA after the ECFA is subject to two key identification challenges: (1) firms may have strategically added ECFA products to their portfolios, and (2) exporters of ECFA items to China differ systematically in size and productivity from those exporting elsewhere.

We thus carry out our treatment analysis focusing on the sample of the firms that ever exported ECFA products. We classify them into treated and control groups based on their history of ECFA export destinations. The treated group consists of firms that consistently exporting ECFA items to China throughout the sample period, directly benefiting from the ECFA tariff reductions. The control group consists of the ECFA exporters that exported ECFA products to countries other than China, while never exporting ECFA items to China. By doing so, we mitigate the biases resulting from (1) the self-selection into export by excluding never-exporting firms and (2) from the strategic product portfolio adjustments post-ECFA. Restricting our analysis to exporters active during 2010 - the year of ECFA implementation - leaves us with a sample of 350 treated and 525 control firms.

We further control for differences in size and productivity using key covariates: (1) PP&E to capture firm size, (2) positive investment rates as a proxy for quantity-based productivity (Olley and Pakes (1996)), and (3) fixed TFP to account for innate market capability differences.

One of our primary objectives is to assess ECFA's impact on within-firm wage dispersion, which is an empirical assessment of the prediction by our conceptual framework: If the markdown responses to the ECFA are more substantial for unskilled labor, a within-firm wage dispersion would increase. In this light, we measure wage dispersion by using two metrics derived from employer-employee matched data: (1) the standard deviation of logged payrolls (SDL) and (2) the coefficient of wage variation (CV):

$$V_{jt}^{SDL} = \sqrt{\frac{1}{N_{jt}} \sum_{ijt} \left(\ln W_{ijt} - \overline{\ln W}_{jt} \right)^2}, \tag{25}$$

$$V_{jt}^{CV} = \frac{\sigma_{jt}^{W}}{\mu_{jt}^{W}}, \tag{26}$$

where W_{ijt} refers to payroll for worker i in firm j and year t; $\overline{\ln W}_{jt}$ is the within-firm average of logged payrolls; σ_{jt}^{W} and μ_{jt}^{W} are the within-firm standard deviation and average of payrolls, respectively.

Table 5 summarizes the sample averages of logged outcome variables and covariates for treated and control firms from 2006 to 2009. Treated exporters exhibit higher wage markdowns for both low-skilled and high-skilled labor (41% and 3.6%, respectively), higher wage rates (31.8%), and higher TFPR (4.17%) relative to controls. In addition, treated exporters show greater within-firm wage dispersion, suggesting a more severe payroll inequality.

However, significant imbalances in covariates reveal a potential violation of the unconditional parallel trends assumption critical for difference-in-differences estimation. For instance, treated exporters were three times larger in PP&E, had higher investment rates (by 3.4pp), and exhibited 2.6% greater fixed TFP compared to controls. Despite carefully selecting control firms that also exported ECFA products, these imbalances in key covariates indicate potential threats to the treatment effects identification. The unbalanced covariates imply that treated and control firms may have had differing growth paths independent of ECFA, thus raising concerns about the validity of the unconditional parallel trends assumption.

Table 5: Treatment Analysis Sample Description:
Averages from 2006 to 2009

	Treated	Control	Difference
Outcome Variables: Performance			
Log Markdowns for Production Worker	0.9439	0.5337	0.4102
Log Markdowns for Non-production Worker	0.0677	0.0319	0.0358
TFPR	-0.0711	-0.1128	0.0417
Log Average Worker Payroll	-0.8432	-1.1610	0.3178
Outcome Variables: Within-Firm Wage Dispersion			
Log SDL of Wage	-0.7256	-0.9729	0.2473
Log Wage CV	-0.6825	-0.9796	0.2971
Covariates			
Log PP&E (normalized)	1.3364	0.0013	1.3351
Positive Investment Rates	0.1188	0.0841	0.0347
Fixed TFP	0.0123	-0.0143	0.0266
No. Treated firms		341	
No. Control firms		263	

Notes: The table presents the sample average of the outcome variables and control covariates for treated and control exporters. The average is calculated based on the observations prior to the ECFA announcement.

To address these issues, we estimate the average treatment effect on treated (ATET) using a doubly robust difference-in-differences estimator (SantAnna and Zhao (2020)). We construct counterfactual outcomes by weighting control firms based on propensity scores of treatment (Abadie (2005)) and perform regression adjustments for outcomes to mitigate biases from potential misspecification of the propensity score model. Pre-treatment averages of capital stock, investment rates, and fixed TFP are employed as covariates in both the propensity score and regression models. This approach closely follows Callaway and SantAnna (2021) and Caetano and Callaway (2024), with key modifications: (1) ECFA was not introduced staggeredly, so we do not need to account for treatment effect heterogeneity across treatment cohorts, and (2) rather than transforming covariates into time-invariant matrices, suggested by Caetano and Callaway (2024), we use pre-treatment averages for propensity score and outcome adjustments to avoid the curse of dimensionality.

Treatment Effect Estimates

Table 6 presents the estimated effects of the ECFA on wage markdowns for low-skilled labor, wage markdowns for high-skilled labor, and TFPR. The doubly-robust ATET estimates indicate that low-skilled labor (e.g., production workers) of treated exporters receive suboptimal wages. Treated exporters exhibited an increase of 9.4% in wage markdowns for low-skilled labor, reflecting enhanced labor market power over low-skilled labor following the ECFA. In contrast, the ECFA did not affect the labor market over high-skilled labor, echoing the comparative static results in Section II. The estimates further reveal the absence of TFPR premiums for treated exporters.

Table 6: Average Treatment Effect of ECFA (Changes in Log): Firm Performance

	Wage Markdowns Low Skilled	Wage Markdowns High-skilled	TFPR
ATET	0.094***	0.034	−0.027
	(0.022)	(0.051)	(0.027)
No. Treated Firms		341	
No. Control Firms		263	

Notes: The table presents the estimated average treatment effects of the ECFA on wage markdowns for low-skilled labor, wage markdowns for high-skilled labor, and TFP. Block-bootstrapped standard errors are in parentheses. Asterisks indicate levels of statistical significance: * 10%, ** 5%, *** 1%.

We further examine the evolution of markdowns between treated and control exporters after the ECFA, as depicted in Figures 2. Consistent with the ATET estimates in Table 6, ECFA-treated exporters experienced only increases in markdowns over low-skilled labor. Wage markdowns over low-skilled labor rose substantially over seven years up to 10%. In contrast, wage markdowns over high-skilled labor flunctuate around the ECFA announcement event, suggesting the absence of the laobr market effect of the ECFA on high-skilled labor.

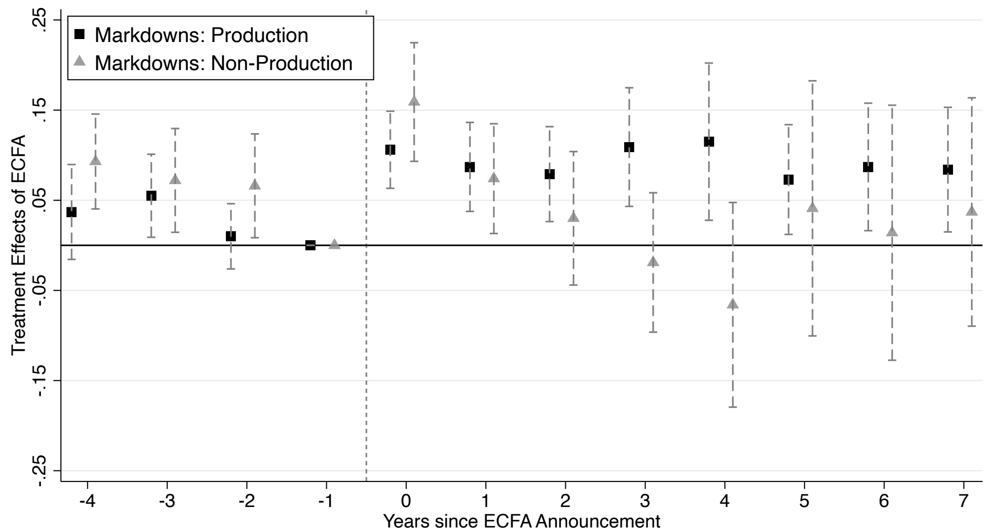


Figure 2: Dynamic Treatment Effects of ECFA: Heterogenous Markdowns

Note. This figure displays the dynamic treatment effects of the ECFA on wage markdowns over low-skilled and high-skilled workers, along with 90% block-bootstrapped confidence intervals. The treatment effects are estimated using the doubly-robust method of SantAnna and Zhao (2020), Callaway and SantAnna (2021), and Caetano and Callaway (2024).

Lastly, we examine how these labor market power effects influence both the between- and within-firm wage dispersions, as outlined in Section II. In the presence of market power in output and labor markets, trade liberalization can exacerbate wage gaps between firms and but also wage gaps within firms due to heterogeneous responses of wage markdowns. When unskilled labor markdowns increase disproportionately more after trade liberalization, this widens the within-firm wage dispersion. To confirm this prediction, we employ the same doubly-robust difference-in-differences design, applying it to the within-firm wage dispersion measures calculated in (25) and (26). Increases in these measures indicate a more right-skewed payroll structure, signifying

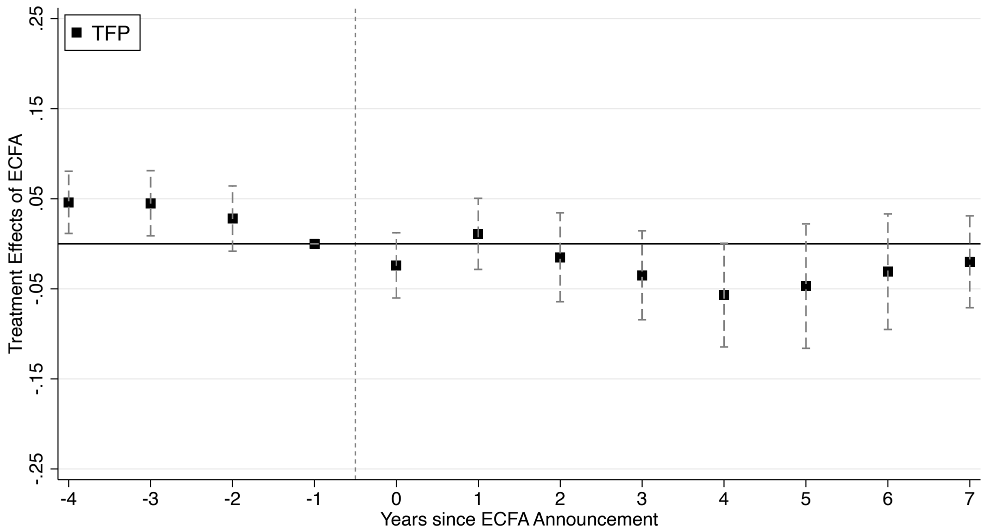


Figure 3: Dynamic Treatment Effects of ECFA: Total Factor Productivity

Note. This figure displays the dynamic treatment effects of the ECFA on TFP, along with 90% block-bootstrapped confidence intervals. The treatment effects are estimated using the doubly-robust method of SantAnna and Zhao (2020), Callaway and SantAnna (2021), and Caetano and Callaway (2024).

higher within-firm worker inequality.

As shown in Table 7, the doubly robust ATET estimates support the theoretical prediction that trade liberalization increases within-firm wage dispersion. First, the average worker payroll at treated exporters rose by 6%, indicating a widening of wage gaps across firms. In addition, employees of ECFA-treated exporters experienced a 5.3% (7.2%) higher standard deviation (coefficient of variation) of wages compared to those at control firms following the ECFA. Thus, despite receiving wage premiums, employees at treated exporters faced greater wage inequalitylikely driven by enhanced labor market power. The dynamic treatment effects on wage levels and within-firm wage dispersion, presented in Figures 4 and 5, further corroborate this pattern.

Table 7: Average Treatment Effect of ECFA (Changes in Log): Payroll Structure

	Wage Rates	SDL of Wage	Wage CV
ATET	0.060***	0.053***	0.072***
	(0.016)	(0.023)	(0.025)
No. Treated Firms		341	
No. Control Firms		263	

Notes: The table presents the estimated average treatment effects of the ECFA on average worker payroll and within-firm wage dispersion measures: the SDL of wage and wage CV. Block-bootstrapped standard errors are in parentheses. Asterisks indicate levels of statistical significance: * 10%, ** 5%, *** 1%.

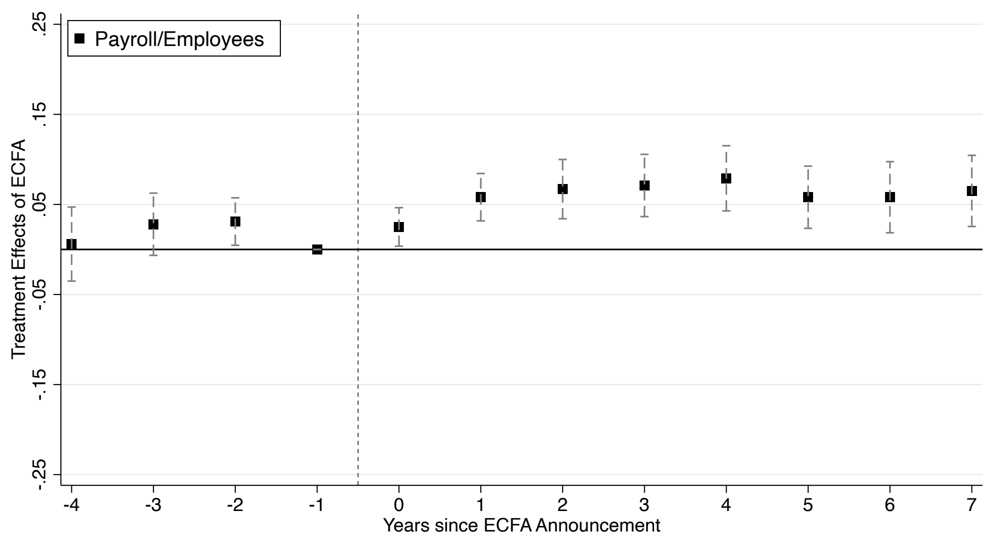


Figure 4: Dynamic Treatment Effects of ECFA: Average Worker Payroll

Note. This figure displays the dynamic treatment effects of the ECFA on the average worker payroll, along with 90% block-bootstrapped confidence intervals. The treatment effects are estimated using the doubly-robust method of SantAnna and Zhao (2020), Callaway and SantAnna (2021), and Caetano and Callaway (2024).

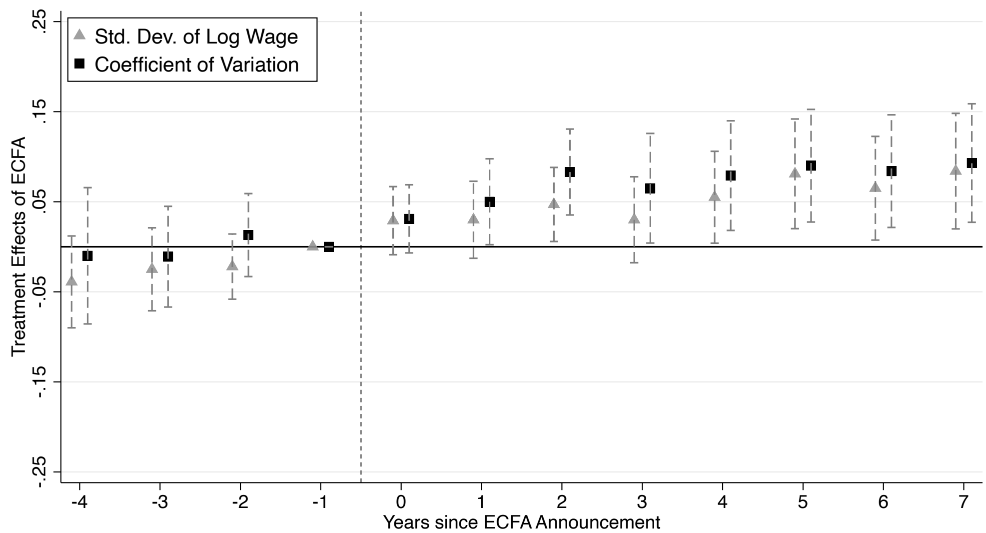


Figure 5: Dynamic Treatment Effects of ECFA: Within-Firm Wage Dispersion

Note. This figure displays the dynamic treatment effects of the ECFA on within-firm wage dispersion, along with 90% bootstrapped confidence intervals. The treatment effects are estimated using the doubly-robust method of SantAnna and Zhao (2020), Callaway and SantAnna (2021), and Caetano and Callaway (2024).

IV Concluding Remark

In this paper, we analyzed the impact of trade liberalization on labor markets when firms can exercise market power. Resources reallocation towards more productive firms after trade liberalization can increase wage markdowns, and heterogeneous responses of markdowns across different types of labor can exacerbate the within-firm wage dispersion. Our findings revealed that the liberalization of export tariffs on transactions with China led to a substantial 9.4% increase in wage markdowns for low-skilled labor within Taiwans machinery and equipment industry. In contrast, the ECFA did not affect wage markdowns for high-skilled labor. We also demonstrated that the resulting heterogeneous exertion of labor market power of firms following the liberalization contributed to greater within-firm wage dispersion, indicating that workers experienced growing payroll inequality.

Our empirical results offer significant implications that extend beyond the Taiwan-China Free Trade Agreement context. First, we highlight the potential welfare distortions arising from trade liberalization, confirming theoretical predictions. The overall efficiency gains from trade liberalization may therefore be modest or even negative in oligopsonistic industries. Given that many modern industries operate under oligopsony conditions, these findings highlights the need for carefully designed trade policies. Second, our analysis illustrates the allocative and distributional effects of international trade within firms, driven by the increased exertion of labor market power. This emphasizes the importance of considering both efficiency and equity when evaluating the outcomes of trade liberalization.

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