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The Effect of Export Market Access on Labor Market Power: Firm-level Evidence from Vietnam*

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Abstract

We examine the impact of an export market expansion created by the US-Vietnam Bilateral Trade Agreement (BTA) on labor market competition among Vietnamese manufacturing firms. We measure distortionary wedges between equilibrium marginal revenue products of labor (MRPL) and wages nonparametrically and find that the median firm pays workers 59% of their MRPL. The BTA permanently decreases labor market distortion in manufacturing by 3.4%, mainly for domestic private firms. The median distortion is 26% higher for women than men, and the decline in distortion for women drives the overall distortion reduction. We shed some light on the mechanisms for these results.

Keywords: International Trade, Export Market Access, Labor Market Distortion, Misallocation, Income Distribution, Labor Share, Gender Inequality, Monopsony, Oligopsony
JEL Codes: F16, F63, O15, O24, J42, J16

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1 Introduction

Many developing and developed countries have experienced a declining labor share of national output in recent decades (Karabarbounis and Neiman, 2014). Some blame for such decline is placed on globalization, although it is surprisingly unclear whether and how globalization is a key contributing factor (see a recent review in Grossman and Oberfield (2022)). This paper adds to the debate above by studying how an export market expansion affects micro-level domestic labor markets and the share of a worker's wage in the additional firm revenue her (his) employment creates via a unique mechanism: labor-market power. The type of labor share we look at is a marginal analog of the simple definition of labor share that is often used.

International trade has been shown to have had large effects on domestic labor market outcomes such as employment and wages in a number of countries (see for reviews Feenstra and Hanson (2001), Harrison, McLaren and McMillan (2011), Goldberg and Pavcnik (2016)). However, only a few studies have directly looked at the effect of trade on firm-level (micro-level) labor shares of output. These include Ahsan and Mitra (2014), Kamal, Lovely and Mitra (2019), and Leblebicioğlu and Weinberger (2021), all of which focus on developing countries such as India and China. In these studies, labor markets are typically assumed to be perfect, or wage is assumed to be determined through firm-worker bargaining or rent sharing. There is, however, a new literature that models imperfect competition in the labor market derived from the labor market power of firms. This modeling approach has been incorporated into the trade literature by either assuming monopsonistic competition (Jha and Rodriguez-Lopez, 2021) or oligopsony (e.g., MacKenzie (2019), Pham (2020), Felix (2021)) in the labor market. In the latter case, where the labor market is oligopsonistic, trade can endogenously affect domestic labor market outcomes, including labor shares, through its impact on labor market competition. Our study develops upon this recent literature.

We first provide a simple theoretical model of trade and oligopsony to convey intuition and guide our empirical analyses. Our model allows for endogenous firm entry into and exit from local labor markets, closely related to Pham (2020), and it provides predictions guiding our empirical work. In the baseline model, firms are assumed to be perfectly competitive in the product market but oligopsonistic in local labor markets. When there is a change in trade barriers, firms enter or exit the industry due to changes in expected profits. Because firms are large in local labor markets, the entry and exit of firms affect the competition for local workers. Thus, a price shock in the product market ultimately affects the distortion in labor markets, where local workers are subject to mobility frictions captured by their (local) aggregate labor supply elasticity.[1] We then extend the baseline model to include two types of workers: men and women, who are taken as separate inputs into a constant-elasticity-of-substitution (CES) production function. We also allow the elasticities of men's and women's labor supplies faced by a firm to be different. The extended model predicts trade's differential impact on men's and women's labor-market distortions.

Two important insights from our model are (1) the lower the elasticity of labor supply for any type of labor is, other things remaining equal, the higher the labor-market distortion, measured as the ratio of marginal revenue product to wage; and (2) firm entry reduces the distortion more for the group of workers with the lower elasticity of labor supply. A key prediction is that when there are two types of workers (e.g., men and women), aggregate labor supply elasticities interact with firm entry to impact labor market distortion. While taken as given in our model, one can think of these aggregate labor supply elasticities at the market level to be dependent on fundamental factors (assumed to be exogenous to our model) such as mobility frictions, the degree of discrimination, barriers to human capital accumulation, and social norms (Hsieh et al., 2019).

Empirically, we apply a nonparametric production function approach to measure firm-level oligopsonistic labor-market distortions using Vietnamese firm-level data from 2000 to 2010 and examine the impacts of an export shock on our measured distortion. Our measure of distortion, the ratio of the equilibrium marginal revenue product of labor (MRPL) to wage, is an inverse measure of labor share at the firm level, conditional on the price-to-marginal cost markup and labor demand elasticity. The MRPL is estimated from a nonparametric revenue production function in which identification is based on a methodology developed by Gandhi, Navarro and Rivers (2020). We then exploit the US-Vietnam Bilateral Trade Agreement (BTA) in December 2001, which resulted in significant tariff reductions by the US on their imports of Vietnamese manufactures (McCaig and Pavcnik, 2018), to examine how that export shock affected the oligopsony-driven firm-level labor market distortion. We describe the US-Vietnam BTA that we use as our natural experiment and

[1] In this paper, we define the "aggregate" labor supply elasticity at the local labor market level. As will be clear in our empirics, we define the local labor market by a 2-digit industry-province cell. However, our reduced-form analyses do not rely heavily on this market definition and alleviate some challenges faced by structural empirical approaches in related literature reviewed below.

several empirical facts surrounding the BTA in Section 2.

Our first two main empirical findings are (1) there exist substantial wedges between equilibrium marginal revenue products of labor (MRPL) and wages in the Vietnamese manufacturing sector, with workers getting paid roughly 59% of their MRPL at the median firm, and (2) firms in industries exposed more to the US tariff reductions see faster employment and wage growth, and a faster decline in their labor market distortion. We find that the BTA permanently decreases the labor market distortion in manufacturing by 3.4%, and the effect concentrates on domestic private firms with a magnitude of 4.9%. Our analysis also provides motivating evidence that the BTA leads to significant firm entry and declines in local labor market concentration.

A unique feature of Vietnamese firm-level data allows us to make several further novel contributions. Vietnamese firm-level data contain consistent information on the gender composition of each firm's workforce. We exploit this information by extending our production function model and measure distortions separately for manufacturing men and women. Two additional findings emerge here. On measurement, we find that the median distortion is 26% higher for women relative to men in that women get paid 52% of their MRPL while men get paid 68% of their MRPL at the respective median firms. However, on the effects of the BTA, we find that the decline in distortion for manufacturing women, amounting to more than 12%, is the primary driver of the overall reduction of the labor-market distortion caused by the trade agreement.

We investigate further to explain why the BTA leads to this larger proportional reduction of firm-level labor market power for women. Our empirical results are consistent with higher aggregate labor supply elasticities for men than for women. We find that the entry of FDI firms following the BTA, combined with these differential aggregate labor supply elasticities between men and women, plays an important role in explaining our results, resonating with the findings in McCaig, Pavcnik and Wong (2022) that FDI firms crucially shape employment composition and employment growth across Vietnam's manufacturing industries.[2] Our results also suggest a stronger interaction between the presence of FDI firms and women's participation in manufacturing. However, we do not find that the effect of BTA on labor market distortion works through industries where women have a comparative advantage, such as textile, fur, and leather, even though these industries indeed see

[2]However, we note here that McCaig, Pavcnik and Wong (2022) perform the employment analysis at the industry level while we investigate at the firm level and look specifically at the competition mechanism and gender dimension.

faster export growth due to the BTA. Instead, the competition effect manifests across the board for Vietnamese manufacturing industries.

Related Literature

Our paper contributes to several strands of literature. First, we build upon the recent literature on trade, labor market competition, and associated misallocation. Several studies include Macedoni and Tyazhelnikov (2018), Jha and Rodriguez-Lopez (2021) and Heiland and Kohler (2019) (theory), and MacKenzie (2019), Pham (2020), Felix (2021) and Gutiérrez (2022) (theory and empirics). These studies differ in assumptions related to: how markets for output and inputs are defined, to what extent markets are correlated, and the competition structure in each market. Different assumptions are often associated with different mechanisms and slightly different predictions. Still, a common result of these studies is that imperfect competition in the labor market can affect welfare gains from trade, and, inversely, trade can affect such competition.[3] In spirit, our theory in this paper is most closely related to Pham (2020), where we effectively assume an orthogonality between the (global) product and the (local) labor market. Because of this structure, the entry of firms directly matters for labor market competition (but not through changes in competition in the product market). We use the theory to guide our analyses and impose mild assumptions on our empirics instead of a more structural approach in MacKenzie (2019), Felix (2021), Gutiérrez (2022).[4]

Second, our paper contributes to the literature on trade and inequality. Specifically, two dimensions of inequality are of concern here. The first dimension relates to the debate on trade's effect on labor's share of output. Even though many studies look at the effect of trade on wages and employment, surprisingly few studies look directly at the impact of trade on labor share at the micro level (Grossman and Oberfield, 2022). Our results suggest that in a small open economy like Vietnam, where trade agreements allow access to new and affluent markets, export market access

[3] Regarding welfare gains from trade, this recent literature is related to an older and larger literature that seeks to quantify gains from trade under the presence of labor market frictions.

[4] The literature that brings together trade and labor market competition is related to a re-emerging literature on labor market power, see for examples, Manning (2003), Card et al. (2018), Berger, Herkenhoff and Mongey (2021). For additional studies that focus on the measurement of labor market power in different countries using various approaches, see Brooks et al. (2021) for China and India, Amodio and de Roux (2021) for Columbia, Hershbein, Macaluso and Yeh (2022) for the US, Amodio et al. (2024) for 82 low and middle-income countries. Amodio, Medina and Morlacco (2022) studies the role of self-employment in shaping labor market power and industrial development in a developing country context, Peru.

increases the marginal income share of workers and, thus, in the aggregate, can increase the total labor share of output through the labor market competition mechanism.

Another inequality dimension relates to the effect of trade on gender inequality. The literature on trade and gender inequality in developing countries suggests that trade can have differing effects on gender inequality, mostly favorable to women relative to men although still context-dependent, and can work through different mechanisms (see Ederington, Minier and Troske (2009), Juhn, Ujhelyi and Villegas-Sanchez (2014), Gaddis and Pieters (2017), Kis-Katos, Pieters and Sparrow (2018), Li (2021) and Wang, Kis-Katos and Zhou (2022) to name a few).[5]

Consistent with the results from the existing literature, we find that export opportunities from the BTA benefit women more than men. However, we contribute a new mechanism to this result: the lower labor supply elasticity for women, in combination with firm entry because of the BTA, leads to greater competition for women than men in the labor market, thus lowering the labor market distortion for women relative to that for men.

Our result of lower labor supply elasticity for women in Vietnam is consistent with previous findings in other settings. Recent work by Sharma (2023) shows that firm-level labor supply is less elastic for women than for men in modern-day Brazil using an oligopsony model, driven by the former's preference to be tied to their existing employer and due to the presence of fewer good employers for them as compared to for men. Sharma (2023) lists the factors responsible for the different nature of labor supply for women in developing countries, including lack of safety, lack of job networks, and gender norms dictating what jobs are appropriate or not for women. Dholakia (1987) also argues that in the case of India, the traditional family system (where the adult women are expected to carry the entire burden of tasks within their respective households) makes the women's labor supply more inelastic. Hsieh et al. (2019) argues that there are three factors affecting individuals' occupational choices (including working in the home sector): discrimination in the labor market, barriers to human capital, and social norms. Thus, the difference in occupational distribution between men and women in the U.S. could arise from historical restrictions on women attending colleges, social norms supporting their role as homemakers, and possible discrimination in the labor market. Intuitively, these factors could also lead to differences in labor supply elasticities.

[5] For the literature on trade and gender inequality in developed countries, see for example Black and Brainerd (2004), Sauré and Zoabi (2014), Hakobyan and McLaren (2018), Bøler, Javorcik and Ulltveit-Moe (2018), Brussevich (2018), Besedeš, Lee and Yang (2021).

While we remain agnostic about the sources of differences in labor supply elasticities between men and women in Vietnam, we complement the literature on gender inequality in developing countries with measurements of labor market power distortion and look at the effect of trade on gender inequality along this dimension.

Finally, our paper adds, in general, to the literature on the effects of trade and trade policies on labor-market and development outcomes, and, more specifically, to our understanding of the effects of the US-Vietnam Bilateral Trade Agreement (BTA) on Vietnam's development outcomes. McCaig (2011) and Fukase (2013) are pioneering studies examining the BTA's impact on Vietnam's poverty and labor markets. Follow-up studies include McCaig and Pavcnik (2013) and McCaig and Pavcnik (2018), which look at the outcomes such as structural change and informality. Mitra, Pham and Ural Marchand (2022) and McCaig, Nguyen and Kaestner (2022) look at intergenerational occupational mobility and children's human capital, respectively. Most closely related to ours is McCaig, Pavcnik and Wong (2022), which investigates the effect of BTA on the long-run industry employment growth and its growth composition based on firm types using Vietnam's firm-level data. They highlight that foreign-invested firms (FDI) played a key role in reshaping the employment composition of Vietnamese manufacturing after the BTA. Our analysis shows that FDI firms explain many of the observed changes in labor market distortion, consistent with findings in McCaig, Pavcnik and Wong (2022). Interestingly, our firm-level analysis in the sample period from 2000-2010 suggests that the effects on labor market distortion manifest in domestic firms but not the FDI firms themselves. We discuss these results in our subsequent analyses.

The paper is organized as follows. Section 2 describes the US-Vietnam BTA that we use as our natural experiment and several empirical facts surrounding the BTA. Section 3 provides a simple model of trade and oligopsony that allows for endogenous firm entry and exit with an extension to two types of workers. Section 4 and 5 describe the data and our measurement method. Section 6 discusses measurement results. Section 7 provides regression analyses of the BTA. Section 8 discusses some mechanisms, and Section 9 concludes.

2 BTA and Vietnam's Export Expansion

The United States-Vietnam Bilateral Trade Agreement (BTA) took about five years to negotiate and went into force in December 2001. The trade agreement was negotiated following the formal normalization of diplomatic relations between the US and Vietnam, which started in 1995. Following the BTA, the most important change on the US side was to grant Normal Trade Relations (NTR)/Most Favored Nation (MFN) status to Vietnam and allow Vietnam's exports immediate access to the US market. In exchange, Vietnam made extensive commitments to change its laws, regulations, and administrative procedures to comply with international trade norms and standards. However, due to its status as a developing country, Vietnam's commitments were "phased-in", meaning that they were scheduled for implementation gradually following the BTA. Although Vietnam also committed to cutting tariffs for 250 out of more than $6,000$ HS-6 US products, its average tariff reductions were negligible since it had already applied low tariffs on imports from the US before the BTA.[6]

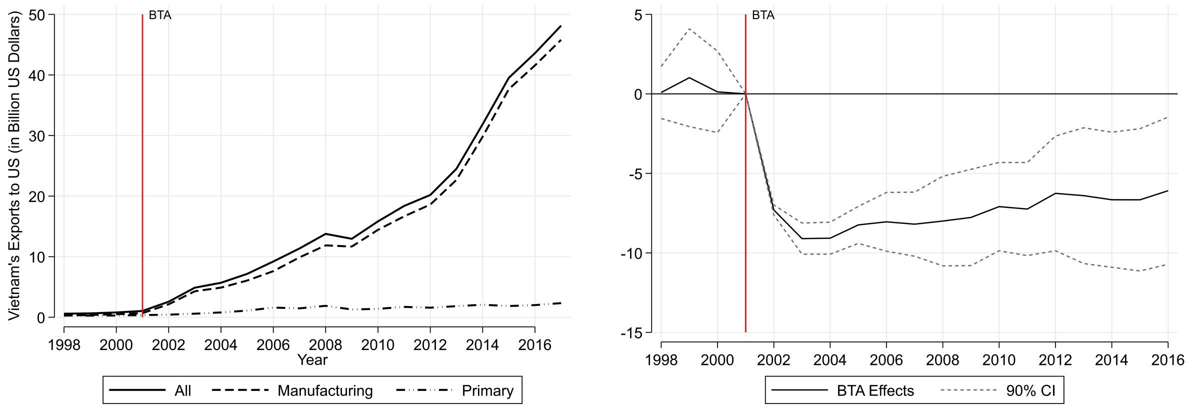
Upon being granted NTR/MFN status, Vietnam was moved from "Column 2" to "Column 1" (MFN) of the US tariff schedule. Importantly, although the BTA was subjected to a lengthy negotiation process on both sides, the magnitude of changes to US tariffs on imports of Vietnamese products was largely *predetermined* and not influenced by either the US or Vietnam's bargaining positions. In particular, the "Column 2" tariffs are those assigned to nonmarket economies under the Smoot-Hawley Tariff Act of 1930. On the other hand, the MFN tariffs are those offered to all WTO members by the US and were determined through a multilateral bargaining process with other countries long before 2001.[7] To this extent, the BTA tariff reductions by the US on Vietnamese products are plausibly exogenous to any domestic conditions or political processes within Vietnam (McCaig, 2011; Fukase, 2013; McCaig and Pavcnik, 2018).

The BTA tariff reductions are also large in magnitude. Following the BTA, the ad valorem US tariffs on Vietnam's products went down from an average of 23.4% to 2.5% at the 2-digit industry

[6] 80% of these 250 tariff concessions were in the agriculture sector.

[7] Upon China's accession to the WTO in 2001, China was guaranteed Column 1 US tariffs (that their exports were already facing but without any certainty in the future that tariffs would not be raised to higher Column 2 ones), thereby eliminating the positive probability of being moved to column 2. In the case of China, this change is interpreted as the removal of trade policy uncertainty rather than an actual trade policy change (as in the case of Vietnam). See also Pierce and Schott (2016) for details.

Figure 1: Vietnam's Exports to the US from 1998-2016 following the BTA



(a) Vietnam's Exports to the US

(b) Changes in Vietnam's Manufacturing Exports Due to BTA

Notes: Panel (a) shows the value of Vietnam's exports to the US during 1998-2016. The primary sectors include agriculture and mining. All values are in nominal terms. Panel (b) plots the effects of the BTA shock on Vietnam's manufacturing exports to the US at the 10-digit product level across years. The effects are obtained from the regression $\ln(Exports)_{ht} = \sum_{y=1998, y\neq 2001}^{2016} \theta_y \mathbb{1}\{y = t\} \times \tau_j^{BTA-gap} + \lambda_h + \lambda_t + \varepsilon_{ht}$, where h is the HS 10-digit level product category and $\tau_j^{BTA-gap}$ is the BTA tariff change measured at 2-digit industry level. The graphs are based on authors' calculations with the trade data from the US Census.

level. The decrease was the largest for the manufacturing sector, from an average of 33.8% to 3.6%, and was much more modest for agriculture and other primary sectors. BTA tariff changes across 2-digit manufacturing industries are shown in Figure A1.[8] As we will show next, the BTA was followed by immediate and extensive growth in Vietnam's manufacturing exports to the US.

Vietnam's Exports to the US

Panel (a) of Figure 1 shows the value of Vietnam's exports to the US from 1998 to 2016. Prior to the BTA, exports to the US were about 1.04 billion US dollars, accounting for only 6.5% of total exports and 3.2% of GDP in 2001. In 2002, immediately after the BTA came into force, exports to the US grew to 2.6 billion US dollars, a 147% increase. By 2006, annual exports to the US amounted to 9.2 billion US dollars, a nine-fold increase since 2001, and accounted for 23% of total exports and almost 14% of GDP. By 2016, Vietnam exported 43.6 billion US dollars to the US, which represented 20% of total exports and almost 21% of GDP. Figure 1 also shows that the

[8] Throughout our analyses, we use the BTA tariff data at the 2-digit industry level for reasons explained in Section 4 and 5, although our main results remain qualitatively similar using the 4-digit BTA tariff data.

bulk of the increase in Vietnam's exports to the US is in manufacturing. Specifically, the share of Vietnam's manufacturing exports in total exports to the US increased from an average of 40% before the BTA to around 67% in 2002 and 87% in 2006, respectively. By 2016, almost the entire portfolio was manufacturing as this share increased to 92%.

To further illustrate the strong and significant effects of BTA on Vietnam's exports to the US in the years after 2001, we consider the following regression:

$$\ln(Exports)_{ht} = \sum_{y=1998, y\neq 2001}^{2016} \theta_y \mathbb{1}\{y=t\} \times \tau_j^{BTA-gap} + \lambda_h + \lambda_t + \varepsilon_{ht}, \tag{1}$$

in which $\ln(Exports)_{ht}$ is the log of exports of the 10-digit manufacturing product category h in year t. $\tau_j^{BTA-gap}$ is the BTA tariff change measured at 2-digit industry level j, which is computed as the difference between the Column 1 and Column 2 US tariffs (see a more formal definition of this gap later in section 7). λ_h and λ_t are product and year fixed effects, respectively. We plot the estimates of $\hat{\theta}_y$ in the panel (b) of Figure 1.[9] As demonstrated in this figure, the effects of BTA were immediate and significant. The coefficients imply that a one percentage point reduction in the BTA tariff led to a 7 to 9 percentage point increase in exports. The effects overall brought about a 180% increase in Vietnam's exports to the US by 2006 and remained permanent afterward.[10]

3 Theory

In this section, we develop a simple equilibrium model of export market access with firm entry and oligopsony in the local labor market. We start with a baseline model where workers are treated as a single human capital input and then extend it to allow for two types of workers: men and women. We assume that a continuum of symmetric firms populates a domestic tradable goods sector, and firms are price takers in the goods market. We also assume that the home country is a small open economy, so home firms take world prices as given. On the other hand, firms are allocated to a continuum of symmetric local labor markets, and within each local market, the number of firms is finite. This setup allows us to focus on modeling the equilibrium within each local market while

[9] Note that in regression equation (1), the coefficient for the year 2001 is omitted as it is taken to be the base year (i.e., $\hat{\theta}_{2001} = 0$). Standard errors are two-way clustered at the 2-digit industry and year level.

[10] Our results from estimating equation (1) are robust to using a PPML regression or BTA tariff changes at more disaggregated levels.

the aggregate economy's outcomes can be easily inferred from the local market outcomes.

Let $Q(L_i) = AL_i$ denote the production of firm i with L_i denoting the number of workers employed by the firm and A denoting the productivity.[11] Let us assume that the inverse aggregate labor supply that the sector faces (in a particular local labor market) is as follows:

$$W = B\mathbb{L}^{\frac{1}{\eta}} = B(\sum_{i=1}^{N} L_i)^{\frac{1}{\eta}} \equiv W_i, \tag{2}$$

where N is the number of firms in an industry (sector) in the local labor market, $\mathbb{L} = \sum_{i=1}^{N} L_i$ is the aggregate labor supply faced by those firms, and η is the aggregate labor supply elasticity. Let $\bar{P}(\tau) = \frac{1}{(1+\tau)}P$ denote the price in the goods market, and τ is the tariff that a foreign country imposes on domestic firms' goods. Firm i's maximization problem is:

$$\max_{L_i} \pi = \bar{P}(\tau)Q(L_i) - W_i L_i \tag{3}$$

$$= \bar{P}(\tau)Q(L_i) - B(\sum_{i=1}^{N} L_i)^{\frac{1}{\eta}} L_i, \tag{4}$$

The first-order condition (FOC) yields:

$$MRPL_i - W_i[1 + \frac{1}{\eta}\frac{L_i}{\sum_{i=1}^{N} L_i}] = 0, \tag{5}$$

where $MRPL_i = \bar{P}(\tau)Q'(L_i) = \frac{1}{(1+\tau)}PQ'(L_i)$. Simplifying and using the symmetry condition, we have:

$$\chi = \frac{MRPL}{W} = \Big(1 + \frac{1}{\eta N}\Big). \tag{6}$$

By the setup of the model, the firm-level equilibrium indicates that the distortionary wedge between MRPL and wage is a function of aggregate labor supply elasticity η and the number of firms N. From the FOC, the equilibrium firm-level employment can also be obtained as:

$$L = \frac{1}{N}\Big[\frac{\bar{P}(\tau)A}{B\Big(1 + \frac{1}{\eta N}\Big)}\Big]^{\eta}. \tag{7}$$

[11] By omitting capital in this production function, we assume that capital is taken as given when firms choose labor, and frictions in capital markets are uncorrelated with frictions in the labor market. We will account for capital in our subsequent empirics (in measuring MRPL and controlling for capital in robustness checks when appropriate) that is consistent with this framework.

Note that aggregate employment NL is increasing in both labor supply elasticity (at the local labor market level) and the number of firms in the local labor market, both of which lead to lower labor market power of firms. The wage, which equals $\frac{(\bar{P}A)}{\chi}$, is increasing in firm productivity, the final-good price, and the number of firms.

To derive the equilibrium number of firms, we next impose the free-entry condition, $\pi^* = f_E$, where $f_E > 0$ is the fixed entry cost. Combined with the production function and FOC, we obtain the equilibrium condition for N^*:

$$\frac{1}{N}\Big[\frac{\bar{P}(\tau)A}{B\Big(1+\frac{1}{\eta N}\Big)}\Big]^{\eta}\Big[\bar{P}(\tau)A - \frac{\bar{P}(\tau)A}{\Big(1+\frac{1}{\eta N}\Big)}\Big] = f_E \tag{8}$$

It also can be shown that $N^{*'}(\bar{P}(\tau)) > 0$. The intuition is straightforward. When the price in the goods market increases, this increases profitability and induces entry of domestic firms. Since the distortion is a direct function of the number of firms, the change in good market price leads to firms reducing the distortionary wedge.

Equilibrium with Two Types of Workers: Men and Women

We can now extend the simple model above with two human capital inputs: men and women. To do this, we specify a CES production function as follows:

$$Q_i = A(\kappa U_i^{\frac{\sigma-1}{\sigma}} + (1-\kappa)V_i^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}, \tag{9}$$

where U and V denote the number of men and women employed, respectively. $\sigma > 0$ is an elasticity of substitution parameter and $\kappa \in (0,1)$ is a comparative advantage parameter.

We specify the aggregate inverse labor supply functions for men and women as follows:

$$W^U = B^U(\sum_{i=1}^{N} U_i)^{\frac{1}{\eta^U}} \tag{10}$$

$$W^V = B^V(\sum_{i=1}^{N} V_i)^{\frac{1}{\eta^V}} \tag{11}$$

Here, we assume that the aggregate labor supply is more elastic for men relative to women $\eta^U > \eta^V$, which will be consistent with measurement results we obtain in Section 6. Firms choose the number of men and women to maximize profit:

$$\max_{U_i,V_i} \pi = \bar{P}(\tau)A(\kappa U_i^{\frac{\sigma-1}{\sigma}} + (1-\kappa)V_i^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \\ - B^U(\sum_{i=1}^{N} U_i)^{\frac{1}{\eta^U}} U_i - B^V(\sum_{i=1}^{N} V_i)^{\frac{1}{\eta^V}} V_i. \tag{12}$$

The FOC for U_i and V_i yields two conditions similar to equation (6):

$$\chi^U = \Big(1 + \frac{1}{\eta^U N}\Big) \tag{13}$$

$$\chi^V = \Big(1 + \frac{1}{\eta^V N}\Big). \tag{14}$$

The relative distortion between these two kinds of workers can then be expressed as:

$$\frac{\chi^U}{\chi^V} = \frac{\Big(1 + \frac{1}{\eta^U N}\Big)}{\Big(1 + \frac{1}{\eta^V N}\Big)} \tag{15}$$

When the aggregate labor supply is more elastic for men relative to women $\eta^U > \eta^V$, this equilibrium ratio has two economic implications. First, $\frac{\chi^U}{\chi^V}$ will be smaller than 1. That is, firms will exercise more market power over women. Second, when the price in the goods market increases due to a reduction in tariffs that leads to firm entry, the entry of new firms will narrow the distortion gap between men and women: $\frac{d(\frac{\chi^U}{\chi^V})}{dN} > 0$.

4 Data

Firm-level Data We use the Vietnam Enterprise Survey (VES) data for 2000-2010 collected by Vietnam's General Statistics Office (GSO). The GSO conducts the VES annually and contains a wide range of information, including firm identification (ID), ownership types, industry classification, geographical information, sales, employment, total labor compensation, material expenditures, and capital stock. The survey unit is a registered enterprise with an independent business account. Thus, different branches under the same company that file taxes separately are treated as distinct business entities. We treat these business entities as firms. All firms or business entities must fill out the survey by law.

We construct a panel data set by linking firms across years using an ID series generated by the GSO. The cleaned unbalanced panel in manufacturing includes about 38.5 thousand firms (with average employment greater than ten workers) spanning 11 years. An important advantage of the VES data is that they contain consistent information about labor composition, particularly gender composition, which we exploit to estimate MRPL separately for men and women.[12] On the other hand, a drawback of the VES data is that they do not contain consistent information about firms' exporting status, somewhat limiting our ability to explore along this firm-level dimension.[13] Appendix A details our data filtering process. Table A1 provides basic descriptive statistics of our cleaned manufacturing sample, including the number of firms, employment, and gender composition across years. It shows that the number of firms increases threefold, and average firm size decreases by about 33 percent while the aggregate gender composition remains stable. Another drawback is that the VES data do not separately contain wage data for men and women. We overcome this problem by estimating cross-section gender wage gaps and imputing these gaps for firms in each 2-digit industry-year cell. We elaborate on this estimation procedure in Section 5. Intuitively, the procedure is to regress the firm-level average wage on gender composition to estimate the gender wage gap for each cell, using the variation in gender composition across firms to predict the premium paid to men over women. We use those premia to compute actual wages paid by gender for each firm.

Tariff Data Our BTA tariff data are obtained from McCaig and Pavcnik (2018) and McCaig, Pavcnik and Wong (2022).[14] In our analyses, we use the BTA tariff data at the 2-digit industry level as the level of tariff shocks. Several reasons justify this choice. First, in our manufacturing data, there are about 9% of firms that "switch" 4-digit industries across the years. These are typically multiproduct firms that report only the industry where they obtain the most revenue in a particular year (as instructed by the VES). Although we do not find that the switching pattern responds to BTA tariff changes, at the 2-digit level, the incidence of switches gets reduced to less

[12] In some years, the data also contain information on the formal and informal status of workers and the skill composition of their workforce. However, this information is not consistent throughout our sample years.

[13] Information on exporting status is only available in 2000, 2002, 2003, 2004.

[14] BTA tariff data (based on VSIC 1993) are available at 2-digit, 3-digit and 4-digit industry levels from Brian McCaig's website at https://sites.google.com/site/briandmccaig/notes-on-vhlsss.

than 4%. On the other hand, BTA tariff variation at the 2-digit level accounts for the majority (60%) of all 4-digit tariff variation within manufacturing.[15] We also check the robustness of our analysis by dropping all firms that switch 2-digit industry affiliations or reassigning their 2-digit industry affiliation to the initial industry. We find that our results remain robust in both cases. Second, and equally crucial for our purpose, since we need to estimate the gender wage gaps for firms at each industry-year cell, analyses at the 4-digit level don't allow us to estimate these gaps precisely for many of the cells, even after using a moving average approach to increase the number of observations as explained in Section 5. Analyses at the 2-digit industry level overcome this problem. For the baseline results that don't require gender wage gap estimation, we also check and find that our results are robust to 4-digit level analyses.

Labor Market Institutions and Location Units Implicit in our theory and empirics is the assumption that labor market frictions exist such that they prevent perfect labor mobility between local labor markets, which in turn gives rise to firms' labor market power. Even though we are unaware of any work that quantifies these frictions and the resulting migration cost of workers, Vietnam's labor market institutions during our sample period suggest that labor market frictions are substantial. One of the main barriers to internal migration is the *ho khau* (household registration) system. The *ho khau* system (dated back to 1955 in Northern Vietnam and applied nationwide after 1975) is a central planning tool the Vietnamese government uses to control population mobility (and resource distribution under the centrally-planing economy before 1986). Under this system, each person is tied to her/his *ho khau* registration location and has limited access to employment opportunities, social services (such as education and healthcare), land rights, and other social entitlements outside of that location. Although *ho khau* laws and regulations change and become less stringent over time, the system still exists today and is an important topic of concern for reforms (see Hardy (2001), Le, Tran and Nguyen (2011), Giang (2013), Nguyen (2016) for more details).

In our sample period, the system's enforcement varies locally, sometimes at the district level, but at the broadest level, the place of registration is best distinguished across provinces and central cities. For this reason, we choose provinces/central cities as location units for the labor

[15] Figure A1 in the Appendix illustrates BTA tariff variation across 2-digit industries.

market, commonly referred to as "provinces". We create a concordance containing 60 consistent provinces/central cities in the data.[16] Combined with the industry dimension, a local labor market is constituted by a 2-digit industry(j) $\times$ province(p) cell. This definition also assumes that labor mobility is costly across 2-digit industries, which is typically the case in developing countries (see, for example, Artuc, Lederman and Porto (2015)).[17] In our subsequent analyses, where appropriate, we control for location-year fixed effects to partial out changes in the supply side of the labor market and focus on the demand-side impacts of export market access, which works through the firm's industry attachment.

5 Empirical Models to Measure Distortion

We begin by specifying a revenue production function of a firm in the log form as follows:

$$r_{it} = f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it}, \tag{16}$$

where $r_{it}, k_{it}, l_{it}, m_{it}$ are the natural logs of revenue, capital, labor, and material of firm i at time t. ω_{it} measures the revenue productivity, i.e., revenue TFP, and ε_t is a random measurement error. Here, $f(.)$ is a revenue production function and is allowed to be nonparametric. We also assume that $f(.)$ is differentiable at all $(k_{it}, l_{it}, m_{it}) \in \mathbb{R}^3_{++}$.

Estimating a revenue production function as in equation (16) is a reasonable approach to measuring labor market distortion for three reasons. First, the specification of the (log) revenue production function in equation (16) could be micro-founded within a large class of demand structures that dictate the firm-specific price as a power function of quantity (see for an example De Loecker (2011)). Second, because we are interested in measuring labor market distortion, we only require information on revenue and wage and, in principle, do not need information on product prices, which is rare. In addition, in the presence of multi-product firms and/or differentiated goods, revenue is a natural aggregation function across different products. This helps avoid challenges in estimating production functions for these firms.[18]

[16] Central cities are equivalent administrative units to provinces, including Hanoi, Da Nang, and Ho Chi Minh.

[17] In a supplemental analysis, we do not find any local spillover effect of the BTA from one industry to firms in another industry in terms of labor market outcomes, consistent with high mobility cost across industries. We omit those results to focus on our main findings, but they are available upon request.

[18] See also this revenue production function approach justified and used by Pham (2020), Amodio et al. (2024).

We also need to make explicit some additional assumptions on the functional form in (16) for our estimation to be valid. The specifications represented by equation (16) implicitly assume that productivity shocks and demand shocks to each firm are Hicks-neutral. On the former issue, there is some evidence that productivity shocks can have non-neutral implications (Doraszelski and Jaumandreu (2018), Zhang (2019), Raval (2019), Lee, Lovely and Pham (2023)). We abstract from this issue since identifying production function in that case requires either a different set of assumptions, an explicit technological shock, or better data. On the latter issue, the BTA tariff is a demand shock that can affect production elasticities (i.e., it nonlinearly affects revenue through production, not just via demand), potentially affecting our subsequent regression results. We empirically test and confirm that our estimated production elasticities do not respond to the BTA tariff in our data. Another assumption we need to make is that firms are small in the national/global product market. This assumption allows us to abstract from any form of interdependence in the demand function so that the estimated production elasticities are valid.[19]

We now briefly describe how we estimate the production function in equation (16). To this end, we adopt the nonparametric identification and estimation method developed by Gandhi, Navarro and Rivers (2020), henceforth, the GNR method. This approach is also adopted and modified by Pham (2020) to estimate a revenue production function using Chinese firm-level data.

Our estimation procedure is implemented in two stages. In the first stage, the firm's profit-maximizing behavior with respect to material is exploited to provide identification information for the revenue elasticity of material, i.e., $\frac{\partial r(.)}{\partial m}$. The intuition is that when firms maximize profit with respect to factor inputs, revenue elasticities have to be equal to expenditure shares for all factors that are *not* subject to market frictions.[20] Following GNR, in the first stage, we estimate the following share-regression using a nonlinear least-square (NLS) procedure:

$$log(s_{it}^M) = log\frac{\partial}{\partial m}f(k_{it}, l_{it}, m_{it}) - \varepsilon_{it}. \tag{17}$$

[19]This assumption would generally be needed in any form of production function estimation where quantity data are not observed.

[20]In this case, we assume that the market for material is relatively frictionless, and hence, the material expenditure share is informative about the revenue elasticity of this factor. In principle, material could be subject to market frictions as well. To alleviate the concerns about frictions in this market, we control for an extensive set of exogenous state variables and fixed effects that could affect the material demand decisions. Therefore, as long as firms do not possess market power in the material market, estimating their revenue elasticity from expenditure share would be meaningful. This approach is also used in other empirical work, for example, in Halpern, Koren and Szeidl (2015).

In equation (17), s_{it}^M is the expenditure share of material obtained directly from the data, and is defined as $s_{it}^M = \frac{P_t^M M_{it}}{R_{it}}$. The nonparametric elasticity function $\frac{\partial f(.)}{\partial m}$ is approximated by a second-order polynomial sieve. The estimation of equation (17) provides us with two outputs to use in the second stage: the revenue elasticity of material $\frac{\partial \hat{f}(.)}{\partial m}$, and the random shock $\hat{\varepsilon}_{it}$.

In the second stage, the production function is fully identified using a Generalized Method of Moments (GMM) procedure. Specifically, given the estimate of $\frac{\partial f(.)}{\partial m}$ and by simple integration, production function $f(.)$ is identified up to a constant $C(.)$ as a function of k_{it}, l_{it}. This integration is denoted by $D^{\varepsilon}(k_{it}, l_{it}, m_{it})$:

$$\int \frac{\partial}{\partial m} f(k_{it}, l_{it}, m_{it}) dm_{it} = f(k_{it}, l_{it}, m_{it}) + C(k_{it}, l_{it}) \equiv D^{\varepsilon}(k_{it}, l_{it}, m_{it}). \tag{18}$$

Plug the expression in equation (18) back to the original specification of production function in equation (16), we can rewrite the productivity term as:

$$\omega_{it} = (r_{it} - \varepsilon_{it} - D^{\varepsilon}(.)) + C(k_{it}, l_{it}). \tag{19}$$

Following the productivity literature, firm productivity is assumed to follow a flexible Markov process:

$$\omega_{it} = h(\omega_{i,t-1}) + \gamma \mathbf{X}_{it} + \mu_{it}, \tag{20}$$

where μ_{it} is an exogenous productivity shock to the firm at time t. Importantly, the exclusion restriction imposed here is that k_{it} and l_{it} are predetermined and do not respond to μ_{it}. In other words, we assume that capital and labor are subject to planning and chosen based solely on the information about the expected productivity captured by $h(\omega_{i,t-1})$. The only factor that responds to the productivity shock μ_{it} is the material m_{it}, the elasticity with respect to which is already identified in the first stage. The Markov productivity process in equation (20) provides exclusion restrictions needed to identify the function $C(.)$. In the Markov productivity equation, we also control for $\mathbf{X}_{it}$, which is a vector of exogenous state variables facing firm i at time t that affect productivity growth or shift the firm's demand function. More specifically, $\mathbf{X}_{it}$ controls for variables including the BTA tariff τ_{it}^{BTA}, firm's ownership, industry-year and location-year fixed effects.

Denoting $\Psi_{it} \equiv r_{it} - \varepsilon_{it} - D^{\varepsilon}(.)$, and combining equations (19)-(20), we can now rewrite the

Markov productivity process as:

$$\Psi_{it} = -C(k_{it}, l_{it}) + h(\Psi_{i,t-1} + C(k_{i,t-1}, l_{i,t-1})) + \gamma \mathbf{X}_{it} + \mu_{it}. \tag{21}$$

Equation (21) nonparametrically identifies $C(.)$ and $h(.)$, and in turn, provides identification of the revenue production function. Equation (21) is estimated using a GMM procedure. As mentioned above, in our main analyses of the paper, we treat k_{it}, l_{it} (and the vector $\mathbf{X}_{it}$) as exogenous or predetermined in (21), as in the original GNR approach. That is, these inputs are assumed not to be correlated with the productivity shock μ_{it}. A feature of the Vietnamese firm-level data is that it provides the values of labor (employment) and capital stock at the beginning of period t.[21] This offers natural instruments for these inputs, which we use for robustness checks. When using these instruments, all of our results remain qualitatively and quantitatively robust.

Given estimates from the revenue production function, we can now compute the empirical measure of the labor market distortion. Since ε_{it} is a random measurement error and does not affect a firm's labor demand decision, we need to correct for this term in calculating the *expected* revenue. The estimation of equation (17) in the first stage does provide us with an estimate of the measurement error, i.e., $\hat{\varepsilon}_{it}$. The measure of the distortion, therefore, can be computed as:

$$\chi_{it} = \frac{\hat{\beta}^L_{it}}{\hat{\alpha}^L_{it}} = \frac{\frac{\partial \hat{r}(.)}{\partial l}}{\frac{W_{it} L_{it}}{R_{it}} \times \exp(\hat{\varepsilon}_{it})}, \tag{22}$$

where $\hat{\beta}^L_{it}$ denotes the (estimated) revenue elasticity of labor, and $\hat{\alpha}^L_{it}$ denotes the (estimated) labor share of total revenue. A value of $\chi_{it} = 1$ implies no distortion. This final step concludes our estimation procedure for the labor market distortion in our baseline model.

Measure Distortion for Manufacturing Men versus Women

In the extended version of our empirical model, we estimate a revenue production function that treats men and women as two separate sources of human capital input. The production function is specified as follows:

$$r_{it} = f(k_{it}, m_{it}, u_{it}, v_{it}) + \omega_{it} + \varepsilon_{it}, \tag{23}$$

[21] See the Data Appendix A for more details.

where u_{it} and v_{it} are the natural logs of numbers of men and women that firm i employs at time t.[22] The identification and estimation of the extended production function in equation (23) follows straightforwardly from the baseline model using the GNR method. This estimation allows us to obtain separate firm-level MRPL and labor elasticities for men and women. Next, we estimate the cross-section gender wage gaps to calculate each firm's average wage for men and women.

Estimate Cross-Section Gender Wage Gaps We estimate cross-section gender wage gaps by regressing the log (average) wage on the gender composition of workers across firms. Denoting W_{it} as the average wage of firm i at time t, W_{it}^U and W_{it}^V as the average wage for men and women respectively, and S_{it}^U as the share of men's employment, the gender gap regression at the firm level is motivated by the following accounting identity:

$$W_{it} = W_{it}^U \times S_{it}^U + W_{it}^V \times (1 - S_{it}^U) = W_{it}^V \left(1 + \left(\frac{W_{it}^U}{W_{it}^V} - 1\right) \times S_{it}^U\right). \tag{24}$$

Taking logs on both sides, we have:

$$\log(W_{it}) \approx \log(W_{it}^V) + \left(\frac{W_{it}^U}{W_{it}^V} - 1\right) \times S_{it}^U. \tag{25}$$

Assuming men's wage premium to be uniform within a two digit industry j and each time period t, we have the following regression equation:

$$\log(W_{ijt}) = c + \left(\frac{W_{jt}^U}{W_{jt}^V} - 1\right) \times S_{ijt}^U + \zeta \mathbf{Z}_{ijt} + u_{ijt}. \tag{26}$$

We regress $\log(W_{ijt})$ on S_{ijt}^U for all firms within each 2-digit industry-by-year cell to estimate men's wage premium $\left(\frac{W_{jt}^U}{W_{jt}^V} - 1\right)$ in each cell. After obtaining the wage premium estimates $\left(\widehat{\frac{W_{jt}^U}{W_{jt}^V} - 1}\right)$, we impute these wage premia for firms in corresponding cells and calculate the average wages firms pay to each gender group.

Some empirical notes about our gender gap estimation ought to be made here. First, firm and worker heterogeneity can affect cross-section wage variation. For the regression version of

[22] As shown in Table A1, there is a small share of firms each year that employ no men or no women (less than 1%). This creates missing values for these firms when the number of men or women is measured in natural logs. To maintain the same sample of estimation, we approximate the natural logs of numbers of men and women as $u_{it} \approx ln(1 + U_{it})$ and $v_{it} \approx ln(1 + V_{it})$, where U_{it} and V_{it} are the actual counts.

equation (25) to work, we assume that heterogeneity in firm productivity and worker's average ability enters production function as a Hicks-neutral term, in spirit similar to Helpman, Itskhoki and Redding (2010).[23] To account for such heterogeneity, we control for firm ownership and a third-order polynomial of firm size, in addition to location and year fixed effects (where possible) in vector $\mathbf{Z}_{ijt}$.

Second, in our implementation, since we do not have enough firm observations to estimate the gender gap for some 2-digit industry-by-year cells precisely, we use a moving average approach to increase the number of observations in each cell. In particular, we use data in industry j for year t and $(t+1)$ to estimate the gap for year t. For example, we use industry j's data for 2000 and 2001 to estimate the gap for 2000, data for 2001 and 2002 to estimate the gap for 2001, and so on. This approach allows us to have at least two years before the BTA for our regression analyses and precisely estimate the gaps for most cells.[24] We also check robustness with multiple alternative approaches to estimate the gaps, including using only current-year data but dropping noisy industry-year cells; controlling for firm, province, year-fixed effects combination; and 3-year moving averages. In each case, all our subsequent regression results remain robust. Nevertheless, the gap estimates' level and interpretation can change depending on specifications. Here, we choose the simplest approach for ease of interpretation.

6 Measurement Results

Table 1 reports the empirical results for the revenue elasticities and labor market distortion across 19 two-digit Vietnamese manufacturing industries. Since our production function is nonparametric, we can recover the distribution of each revenue elasticity and the firm-level distortion within each industry. Across all industries, our estimation procedure produces a median capital elasticity of 0.07, labor elasticity of 0.25, and material elasticity of 0.73. The median magnitude of the labor market distortion χ estimated for Vietnam's entire manufacturing sector during our sample period is 1.70, implying that a worker got paid 59% of additional revenue he/she brought to the median firm. The average value of estimated distortion is 1.64, indicating that the distribution of firm-level

[23] We also need this assumption to measure and interpret the labor market distortion correctly. See also Pham (2020) for a more detailed exposition.

[24] For 2010, we have sufficient observations to estimate the gaps for cells in this year.

Table 1: Revenue Elasticities and Labor Market Distortion by Industry

Industry (2-digit)	Capital	Labor	Material	RTS	χ Mean	χ Median	No. Obs
15.Food-Beverages	0.07	0.22	0.76	1.05	1.44	2.07	21348
17.Textile	0.08	0.27	0.70	1.04	2.21	1.98	6959
18.Fur	0.12	0.38	0.55	1.05	1.27	1.08	12071
19.Leather	0.12	0.36	0.58	1.05	1.42	1.20	3717
20.Wood	0.08	0.28	0.69	1.05	1.99	1.88	9732
21.Paper	0.05	0.19	0.80	1.03	2.22	2.21	7084
22.Printing	0.06	0.24	0.75	1.05	1.63	1.62	5808
24.Chemicals	0.04	0.15	0.84	1.03	0.91	1.38	6719
25.Plastics	0.05	0.19	0.80	1.03	1.87	1.96	9899
26.Minerals	0.10	0.34	0.61	1.05	2.00	1.79	13309
27.Metal-Processing	0.03	0.14	0.86	1.03	0.74	1.70	2784
28.Metal-Products	0.05	0.21	0.78	1.04	1.45	1.61	14663
29.Other-Equipment	0.06	0.20	0.78	1.04	1.59	1.56	4434
31.Other-Electronics	0.04	0.15	0.84	1.03	1.32	1.63	2639
32.Radio-TV	0.06	0.23	0.76	1.04	1.16	1.29	1341
33.Medicals	0.06	0.24	0.75	1.05	1.54	1.47	623
34.Motor-vehicles	0.06	0.23	0.75	1.05	1.87	1.88	1917
35.Other-transportation	0.07	0.24	0.74	1.04	1.73	1.74	3461
36.Furniture	0.08	0.28	0.69	1.05	1.81	1.69	10944
All Industry	0.07	0.25	0.73	1.04	1.64	1.70	139452

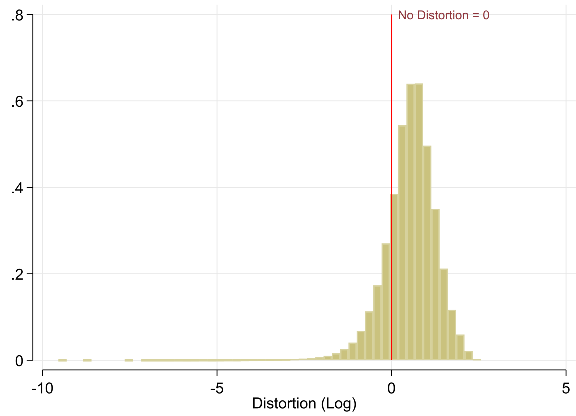
Notes: The table reports estimated statistics of the revenue elasticities of factors (capital, labor, material), the revenue return to scale (RTS), and the measured distortion (χ) from production function estimation in Section 5 (where a value of $\chi = 1$ implies no distortion). All statistics are the median of respective distributions, except for the distortion, where both the mean and median are reported. The table trims observations with the estimated χ outside the 1^{st} and 99^{th} percentiles each year. The last column reports the number of observations for each two-digit industry.

distortion is skewed to the right. Across all industries, the mean and median of the distortion are consistently greater than one, with some industries having these moments higher than others. This empirical fact suggests that Vietnamese manufacturing firms potentially face pervasive frictions and incur large distortions in the labor market during the 2000-2010 period.[25]

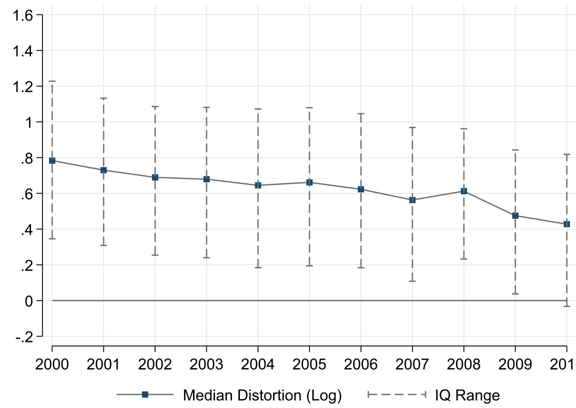
Figure 2 shows the distribution of labor market distortion (in logs) across firms and how this distribution shifts over sample years. Panel (a) of Figure 2 illustrates the distribution of $log(\chi)$ for the whole sample. As demonstrated, most of this distribution is well on the right of zero ($log(\chi) = 0$ corresponds to no distortion). While there is certainly a degree of measurement

[25]Since there can be a certain amount of measurement error coming out of our estimation procedure, we choose to focus on the interpretation of the medians of respective distributions, although we note that the mean values display almost similar magnitudes and trends in all cases.

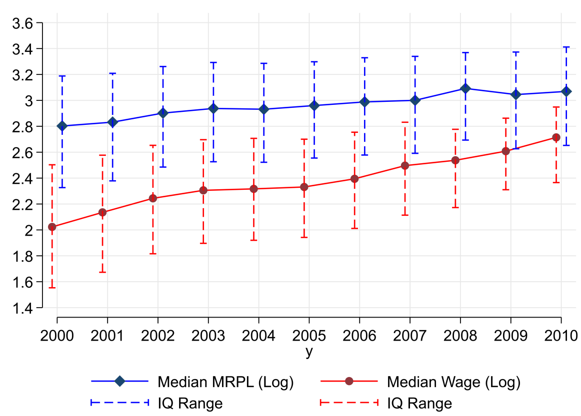
Figure 2: Distributions of Labor Market Distortions in Logs ($\log(\chi)$)



(a) Histogram of $\log(\chi)$ over the Whole Sample



(b) Distributions of $\log(\chi)$ over Time



(c) Distributions of Log MRPL and Wage over Time (in 2000 Prices)

Notes: The figures illustrate the distribution of the log-measured labor market distortion (χ), MRPL, and wage. The first panel shows the distribution of distortion across the whole sample. No distortion cutoff is where $log(\chi) = 0$. The second panel displays the evolution of distortion distribution over our sample period via median and interquartile range. We trim the estimated χ outside the 1^{st} and 99^{th} percentiles each year. The last panel displays the evolution of log MRPL and log wage measured in 2000 prices (Million Vietnam Dong).

error from production function estimation and wage data, the significant portion of distortion distribution on the right of zero suggests a high degree of distortion in the labor market. This fact is further illustrated in Panel (b) of Figure 2. This second panel displays the evolution of labor market distortion distribution over time. Across the sample period, distortion distribution has shifted significantly closer to zero, with decreases in both the mean and median, implying that efficiency loss due to the labor market distortion in Vietnam has declined over time.[26] We find

[26]This result resonates the findings in Pham (2020) for China's manufacturing sector. However, we do not find

that the median distortion declines from 2.09 in 2000 to 1.44 in 2010. Although the magnitude of the distortion remains significant in 2010, the decline corresponds to 35 log points. When we decompose the decline into separate changes in real MRPL and real wage in Panel (c), we find that both changes in real MRPL and wage account for this decline in distortion. While the real median MRPL has increased by about 27 log points, the real median wage has risen by about 69 log points, significantly narrowing the distortion wedges between MRPL and wage from a technical point of view.

Table 2 correlates the firm-level measured distortion with measured productivity, employment size, women's employment share, local labor market concentration (measured in wage bill), and firm ownership, within industry-year and province-year cells. More productive firms incur a higher level of labor market distortion, regardless of the covariates included. Conditioning on productivity, larger firms are associated with lower distortion. Columns (3)-(4) show that firms with higher women's employment shares incur more distortion (conditioning on the firm's employment size and/or productivity), and firms located in markets with higher concentration incur more distortion. In addition, we also find that private firms are more distorted in the labor market, relative to state-owned firms, while foreign-owned firms appear not to be more distorted.[27]These correlations provide background for our subsequent empirical findings and narratives.

Manufacturing Men versus Women

As described in Section 5, we estimate the labor market distortion separately for manufacturing men and women using our extended production function, combined with the estimated gender wage gaps. Panel (a) of Figure 3 illustrates kernel densities of the log-measured labor market distortions for men ($log(\chi^U)$) and women ($log(\chi^V)$). In statistical terms, we find that the overall median distortion for women is 26 log points higher than that for men.[28] In economic terms, women get paid 52% of their MRPL while men get paid 68% of their MRPL at the respective median firms. Nonetheless, we find that this gap in distortions across gender narrows down significantly over time, with the median distortion gap decreasing from 29% in 2000 to almost 21% in 2010, as shown in Panel (b) of Figure 3. This trend implies that the labor market for manufacturing women has

that the dispersion of the measured distortion decreased in Vietnam.

[27]When not conditioning on productivity, foreign-owned firms appear to be the least distorted in the labor market.

[28]Similarly, we find that the mean distortion is 19 log points higher for women relative to men.

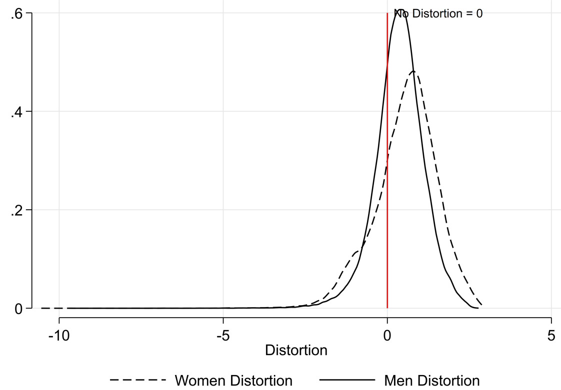
Table 2: Correlations between Measured Distortion and Firm Characteristics

	(1) $log(\chi)$	(2) $log(\chi)$	(3) $log(\chi)$	(4) $log(\chi)$	(5) $log(\chi)$
Log TFPR	1.151***	1.149***	1.157***	1.158***	1.165***
	(0.051)	(0.050)	(0.049)	(0.049)	(0.049)
Log Employment		-0.021***	-0.024***	-0.023***	-0.014***
		(0.004)	(0.004)	(0.004)	(0.005)
Women's Share (Employment)			0.063**	0.063**	0.065**
			(0.026)	(0.026)	(0.027)
HHI (Labor Market Concentration)				0.152***	
				(0.023)	
Private-Owned					0.071***
					(0.015)
Foreign-Owned					0.023
					(0.016)
Observations	129,605	129,605	129,605	129,605	129,605
R-squared	0.233	0.234	0.234	0.235	0.235
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the regression results of the measured distortion (χ_i) on firm-level characteristics, controlling for (2-digit) industry×year and province×year fixed effects. The HHI in column (4) is the Herfindahl-Hirschman Index of employer concentration (measured in wage bill) within a province-industry cell. Standard errors are clustered two-way at (2-digit) industry×year and province×year levels (*** p<0.01, ** p<0.05, * p<0.1).

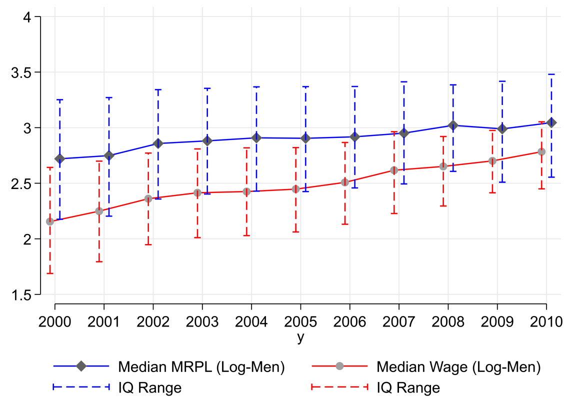
become much more competitive, although the gap persists. In this sense, women were able to get paid much closer to the additional value they brought to the firms. In fact, as shown in the figure, competition in the labor market has improved significantly for both groups but relatively more so for women. The decline in the distortion gaps nonetheless masks the underlying factors that account for this aggregate trend. Interestingly, we find that while the firm-level MRPL gap between men and women has fluctuated and only increased slightly over time, the firm-level wage gap has narrowed significantly, which is the main factor contributing to the aggregate decline in the distortion gap. We show this pattern in Panel (c) and (d) of Figure 3 and Figure C1 in the Appendix. With these measures in hand, we are now ready to examine the causal impacts of the BTA on the measured labor market distortions.

Figure 3: Distributions of Labor Market Distortions in Logs for Manufacturing Men and Women

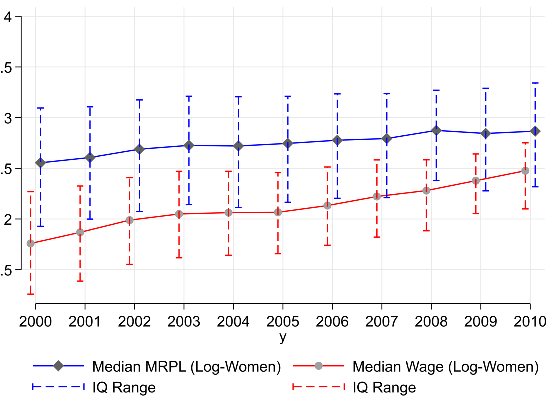


(a) Distribution of Women/Men's Distortion over the Whole Sample (in Logs)

(b) Median of Women/Men's Distortion over Time (in Logs)



(c) MRPL and Wage over Time for Men



(d) MRPL and Wage over Time for Women

Notes: Panel (a) illustrates kernel densities of the log-measured labor market distortion separately for men ($log(\chi^U)$) and women ($log(\chi^V)$) in the manufacturing sector from the extended production function estimation in Section 5. Panel (b) illustrates how the median of distortion for men and women changes over time. Panel (c) and (d) illustrate the distribution of MRPL and wage over time for men and women, respectively. We trim the estimated χ^U and χ^V outside of 1^{st} and 99^{th} percentiles in each year.

7 The Effects of BTA: Regression Analyses

Baseline Regression

A key objective of this paper is to understand how the BTA tariff reductions affected the labor market distortions in Vietnam's manufacturing industries. We begin this section by estimating a baseline difference-in-difference (DID) model as follows:

$$log(\chi_{i(jp)t}) = \theta \times PostBTA_t \times \tau_j^{BTA-gap} + \lambda_i + \lambda_{pt} + \varepsilon_{ijlt}. \tag{27}$$

In equation (27), the dependent variable is the logarithm of measured labor market distortion. $PostBTA_t$ is an indicator variable for post-BTA years (i.e., $PostBTA_t = 1$ if $t \geq 2002$ and $PostBTA_t = 0$ otherwise). $\tau_j^{BTA-gap}$ is the difference (the gap) between the MFN and "Column 2" tariff of industry j and is computed as:

$$\tau_j^{BTA-gap} = \tau_j^{MFN} - \tau_j^{\text{Column 2}} < 0. \tag{28}$$

Here, τ_j^X, with $X \in \{MFN, \text{Column 2}\}$, is defined in natural logs as $ln(1 + \bar{\tau_j}^X)$, where $\bar{\tau_j}^X$ is the standard ad valorem tariff (MFN or "Column 2" tariff) for that industry. λ_i controls for firms' fixed effects, and λ_{pt} controls for province-by-year fixed effects. The coefficient of interest is θ. Intuitively, θ is identified by comparing the outcome variable's differential *changes* across firms within the same province-by-year cell. These firms differ only in their differential exposure to *changes* in BTA tariffs due to their industry affiliations. Standard errors are clustered two-way at firm and industry-by-year levels. In addition to our main outcome of interest, $log(\chi_{it})$, we also examine similar DID regressions with other outcomes to shed light on our results. A negative coefficient in the subsequently reported results means that the BTA increases the outcome variables, since the BTA tariff gap measure always has a negative value (given that the MFN tariff is always lower than the Column 2 tariff).

Local Entry, Exit, and Labor Market Concentration

To begin with our regression results, Table 3 reports estimates of the effect of the BTA on four dependent variables at the market (2-digit) industry-by-province (jp) level: (1) counts of firm entry, (2) counts of firm exit, (3) counts of current number of firms, and (4) Herfindahl-Hirschman Index (HHI) of employer concentration measured in wage bill. This regression resembles that of equation (27), except that we run it at the local labor market level, controlling for market (jp) fixed effect and province-year (pt) fixed effects. Here, we use OLS regressions and take the $\log(1 + y)$ of

Table 3: Impact of BTA on Local Entry, Exit, and Labor Market Concentration

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Dependent Variables in $\log(1+y)$	Entry Counts	Exit Counts	Firm Counts	HHI (Wage-bill)
(Sample Used)	(2001-2010)	(2000-2009)	(2000-2010)	(2000-2010)
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.489***	-0.260**	-0.457***	0.142***
	(0.162)	(0.107)	(0.101)	(0.032)
Observations	7,244	7,055	7,881	7,881
R-squared	0.794	0.778	0.951	0.844
Market (jp) FE	Yes	Yes	Yes	Yes
Province-Year (pt) FE	Yes	Yes	Yes	Yes

Notes: The table reports the results on the effects BTA on local firm entry, exit, counts and wage-bill Herfindahl-Hirschman Index (HHI). Standard errors are clustered at market (2-digit) industry-by-province level (*** p<0.01, ** p<0.05, * p<0.1).

the dependent variables (PPML estimation in levels delivers similar results, which are reported in Appendix Table C1).

Columns (1)-(3) show that entry, exit, and firm counts across local labor markets respond to BTA tariff changes. In particular, BTA tariff reductions cause an increasing incidence of firm entry within a local labor market. The BTA tariff reductions also appear to cause an increasing incidence of firm exit, yet smaller than the effect on entry (about half). The overall net effect is estimated in column (3), where within each local labor market, the BTA shock leads to a significant increase in the number of firms. We also compute the employer concentration HHI index for each market (jp) and regress this index on the BTA shock in column (4). The increase in firm counts due to the BTA translates to a decrease in the HHI index within each local labor market. We find a similar result when regressing firm-level labor market share on the BTA variable: the BTA has led to a decrease in the firm's market share within each local labor market. These results resonate with the previous literature where plant survival rate, growth, and consequential labor market outcomes are found to be associated with trade shocks in other countries (Bernard, Jensen and Schott (2006), Asquith et al. (2019)).

Table 4: Impact of BTA on Firm-level Outcomes

Dependent Variables	(1) $log(L)$	(2) $log(W)$	(3) $log(MRPL)$	(4) $log(\chi)$
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.201***	-0.074*	0.056	0.112**
	(0.056)	(0.039)	(0.047)	(0.045)
Observations	128,406	128,406	118,437	118,437
R-squared	0.911	0.725	0.711	0.609
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes

Notes: The table reports the results of regression equation (27) with four dependent variables: (1) log of employment, (2) log wage, (3) log of MRPL, and (4) log of measured distortion. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** p<0.01, ** p<0.05, * p<0.1).

Firm-level Outcomes: Employment, Wage, MRPL, Distortion

Table 4 reports the results for the baseline DID regressions. Columns (1)-(2) show the results of the regression equation (27), using the log of employment and wage of firms as dependent variables. Column (1) shows that firms that operate in industries more exposed to the BTA tariff reductions see faster employment growth, with an elasticity of 0.201. Column (2) reveals that the BTA has a statistically significant impact on the overall relative wage growth for these firms in our sample period, even though the magnitude of the coefficient is much smaller, of about 0.074. Columns (3)-(4) show the results where the log-measured MRPL and distortion are dependent variables. Column (3) shows that firms more exposed to the BTA see some pressure in MRPL (slower relative growth), although this estimate is not statistically significant. Combining MRPL with the wage response, the BTA leads to a relative reduction in the labor market distortion, as shown in column (4), with an estimated elasticity of 0.112. This is our first key result for the paper. The BTA has led to a reduction in labor market distortion overall. The average decrease in BTA tariff at the 2-digit industry level is 30 log points. This implies that the distortion has decreased by $30 \times 0.112 \approx 3.4$ percent due to the BTA based on a simple calculation.

To break down the response of firms' outcome variables over time, we next estimate a dynamic

Table 5: Impact of BTA on Firm-level Outcomes (Dynamic DID)

Dependent Variables	(1) $log(L)$	(2) $log(W)$	(3) $log(MRPL)$	(4) $log(\chi)$
$\tau_j^{BTA} \times \mathbb{1}\{y = 2000\}$ (2-digit)	-0.170	-0.009	0.021	0.029
	(0.110)	(0.061)	(0.067)	(0.057)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2002\}$ (2-digit)	-0.185**	-0.132***	-0.018	0.094
	(0.078)	(0.051)	(0.058)	(0.063)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2003\}$ (2-digit)	-0.281***	-0.163***	-0.004	0.157**
	(0.071)	(0.053)	(0.063)	(0.069)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2004\}$ (2-digit)	-0.239***	-0.086	0.028	0.080
	(0.077)	(0.061)	(0.058)	(0.071)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2005\}$ (2-digit)	-0.191***	-0.025	0.122**	0.127*
	(0.072)	(0.053)	(0.058)	(0.065)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2006\}$ (2-digit)	-0.265***	-0.043	0.094*	0.108*
	(0.075)	(0.053)	(0.057)	(0.055)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2007\}$ (2-digit)	-0.232***	-0.011	0.029	0.043
	(0.077)	(0.053)	(0.063)	(0.056)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2008\}$ (2-digit)	-0.251***	-0.089	0.059	0.139*
	(0.079)	(0.057)	(0.063)	(0.073)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2009\}$ (2-digit)	-0.191**	0.007	0.160**	0.132**
	(0.095)	(0.053)	(0.066)	(0.064)
$\tau_j^{BTA} \times \mathbb{1}\{y = 2010\}$ (2-digit)	-0.286***	-0.098	0.129**	0.199**
	(0.099)	(0.060)	(0.065)	(0.081)
Observations	128,406	128,406	118,437	118,437
R-squared	0.911	0.725	0.711	0.609
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes

Notes: The table reports the results of regression equation (29) with five dependent variables: (1) log of employment, (2) log wage, (3) log of MRPL, and (4) log of measured distortion. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** p<0.01, ** p<0.05, * p<0.1).

version of our DID model as follows:

$$log(\chi_{i(jp)t}) = \sum_{y=2001, y\neq 2001}^{2010} \theta_y \mathbb{1}\{y = t\} \times \tau_j^{BTA-gap} + \lambda_i + \lambda_{pt} + \varepsilon_{ijlt}. \tag{29}$$

In equation (29), the overall effect of $\tau_j^{BTA-gap}$ obtained from (27) is decomposed by year and allowed to vary over time. This heterogeneity is captured by the interaction terms between $\tau_j^{BTA-gap}$ and the year indicators $\mathbb{1}\{y = t\}$.[29] Table 5 reports the estimation results.

Consistent with the results in Table 4, column (1) shows that employment growth is significantly

[29]The effect of the year 2001 is normalized to 0 as our base year in this dynamic DID specification.

higher for firms in industries more exposed to the BTA tariff reductions. When breaking down by years, column (2) shows that wage growth is significantly higher in these industries as well for the first two years following the BTA (in 2002 and 2003), but the effect becomes statistically insignificant in subsequent years, suggesting that the effect of the BTA on the average firm-level wage might be more immediate. On the other hand, column (3) shows that firms more exposed to the BTA see an initial uptick in MRPL immediately following the BTA but then start to decline (relatively), with the effect becoming more significant and more prominent in the later years in our sample period (since 2005). Column (4) shows that labor market distortions have consistently (relatively) declined for firms more exposed to BTA. This column confirms our key result that the BTA has led to a decline in manufacturing labor market distortion.

Some patterns are worth noting here. First, in the initial years, the effect of BTA on distortion was driven by the wage increase. In the later years, however, the effect of BTA on distortion manifests mainly through an MRPL decrease. These results are consistent with upward-sloping labor supply curves facing firms in the short run, within one- or two-year periods. Second and importantly, the results from columns (1) and (2) can be used as reduced-form validations for our production function measurement of distortion in Section 5 and 6. In our production function approach, we find the median value of distortion in 2001 is 1.96, suggesting workers get paid 51% of MRPL at the median firm. This value is 1.84 for the mean, suggesting workers get paid 54% of MRPL at the average firm, facing an average firm-level labor supply elasticity of 1.2. The immediate responses of wages and employment to the BTA shock (viewed as a labor demand shock) right after 2001 suggest an average labor supply elasticity facing firms of about 1.4, translating to workers getting paid 58% of MRPL. This estimate is very close to our median or mean estimate based on production function estimation. The reduced-form results here thus help to validate our measurement (see also the use of this reduced-form approach to measurement in Berger, Herkenhoff and Mongey (2021), Pham (2020), Amodio and de Roux (2021)). Finally, Table 5 does not indicate any pre-trend pattern for firm outcomes in all columns, supporting the causal interpretation of the estimates.

Table 6: Impact of BTA on Firm-level Outcomes: By Firm's Ownership Types

Dependent Variables	(1) $log(L)$	(2) $log(W)$	(3) $log(MRPL)$	(4) $log(\chi)$
State-Owned Firms				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.026	0.066	0.189	0.122
	(0.148)	(0.077)	(0.131)	(0.132)
Observations	8,957	8,957	8,402	8,402
R-squared	0.948	0.832	0.754	0.700
Domestic Private Firms				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.214***	-0.107**	0.081	0.164***
	(0.069)	(0.045)	(0.051)	(0.048)
Observations	93,689	93,689	86,387	86,387
R-squared	0.860	0.667	0.668	0.589
Foreign-Owned Firms				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	0.037	-0.003	-0.157	-0.162
	(0.119)	(0.079)	(0.103)	(0.108)
Observations	18,042	18,042	16,607	16,607
R-squared	0.939	0.705	0.788	0.693
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes

Notes: The table reports the results of regression equation (27) with four dependent variables: (1) log of employment, (2) log wage, (3) log of MRPL, and (4) log of measured distortion. We run the regression separately for firms with different ownership types. We drop about 5.3% of firm-year observations that entail firms switching ownership, although the results are the same when we include them. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** p<0.01, ** p<0.05, * p<0.1).

Effects by Firm Ownership

Next, we investigate whether BTA's effects on distortion and other firm-level outcomes vary by firm ownership. We investigate the effects for three separate types of firms: State-Own Enterprises (SOE), Domestic-Private (PRI), and Foreign-Owned (FDI). This result is important because the trade literature suggests that different types of firms respond differently to market incentives. In the context of Vietnam, SOE and FDI firms play a significant role in national output, while PRI firms are still relatively underdeveloped. We report the results in Table 6. We find that almost all the effects on labor market distortion and other outcomes come from domestic private firms (PRIs), with the coefficient estimates for this type of firm somewhat larger than those in Table 4. In response to the BTA, private firms in more exposed industries increase employment and wages and reduce the labor market distortion relative to firms in other industries. Nonetheless, this is not true for either SOE or FDI firms. The result that SOE firms are not likely to respond to market incentives is not surprising, given the literature studying the behavior of SOEs in developing countries and how they respond to market incentives such as trade (Hsieh and Song (2015), Baccini, Impullitti and Malesky (2019), Pham (2020)). On the other hand, the fact that FDI firms do not appear to evolve differently (compared to SOEs) due to the BTA is quite interesting, and we will connect this result to the results presented below when we control for industry-level FDI share in the base regression. We note here that this result resonates with the findings in McCaig, Pavcnik and Wong (2022), which shows that the increase of FDI employment share at the industry level following the BTA was driven by new FDI entries rather than continuing FDI firms at least until 2010. We find similar results here using a firm-level analysis.

Effects for Manufacturing Men versus Women

Using our extended measurement results in Section 5, we next estimate regressions in equations (27)-(29) separately for firm-level outcomes regarding manufacturing men and women. The goal is to examine the effects of the BTA separately for these two groups of workers. The regression results are reported in Table 7 and Table 8, respectively.

Columns (1)-(2) in Table 7 show that following the BTA, firms that are more exposed to the BTA tariff reductions see larger employment growth for both men and women. Nonetheless, the magnitude of the effect for women is much larger and is more than double in absolute terms. Columns (3)-(4) show the regression results for wages. Interestingly, while we do not see a statistically significant effect of the BTA on the relative wage growth for men, women's wage growth is significantly faster for firms in industries more exposed to the BTA. Columns (5)-(6) reveal that the MRPL for women also grows relatively slower for firms in these industries, but the response of men's MRPL is mostly muted. Similarly, columns (7)-(8) consequently demonstrate that the effect of BTA on labor market distortions is significant and much larger for women. These results

Table 7: Impact of BTA on Firm-level Outcomes: Manufacturing Men versus Women

	Employment		Wage		MRPL		Distortion	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables	$log(U+1)$	$log(V+1)$	$log(W^U)$	$log(W^V)$	$log(MRPL^U)$	$log(MRPL^V)$	$log(\chi^U)$	$log(\chi^V)$
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.106**	-0.249***	0.058	-0.291***	-0.006	0.126**	-0.077	0.405***
	(0.051)	(0.064)	(0.046)	(0.053)	(0.049)	(0.050)	(0.055)	(0.064)
Observations	125,577	125,577	125,558	125,574	121,348	113,978	121,329	113,975
R-squared	0.889	0.927	0.718	0.731	0.759	0.784	0.637	0.731
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Two-way								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of regression equation (27) with separate dependent variables for manufacturing men (U) and women (V). Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** p<0.01, ** p<0.05, * p<0.1).

suggest that the overall reduction in the labor market distortion shown in column (4) of Table 4 is mainly driven by the decreased labor market distortion for manufacturing women, about 2/3 of the decline in the relative labor-market distortion for women being from the narrowing of the wage gap and 1/3 from the widening of their MRPL gap. We do not find support for a direct response of the distortion for manufacturing men on average to the BTA (as the coefficient is statistically insignificant). Using the simple calculation based on the estimated elasticity again, the distortion for women has decreased by $30 \times 0.405 \approx 12.2$ percent due to the BTA. The overall decrease in distortion of 3.4 percent computed from the baseline regression is thus the net effect of two factors: (1) the increase in the share of manufacturing women following the BTA, which increases the average distortion (because women's labor markets are characterized by higher distortions), and (2) the endogenous decrease in the distortion for women in response to the BTA.

When breaking down the effect of the BTA by year, Table 8 paints a similar picture. While employment growth is relatively faster for both men and women in industries more exposed to the BTA, the magnitude of the effects is larger for women (columns (1)-(2)). In the case of wage (columns (3)-(4)), while both types of workers see initial jumps, the effects of the BTA on men's wages disappear and sometimes reverse in sign in later years, while women see consistent relative wage growth across years. Columns (5)-(6) show that the MRPL for men does not respond to the BTA, while the MRPL for women sees slower relative growth in more BTA-exposed industries, especially in later years since 2005. Columns (7)-(8) further confirm the results in Table 7 that

Table 8: Impact of BTA on Firm-level Outcomes: Manufacturing Men versus Women (Dynamic DID)

	Employment		Wage		MRPL		Distortion	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables	$log(U+1)$	$log(V+1)$	$log(W^U)$	$log(W^V)$	$log(MRPL^U)$	$log(MRPL^V)$	$log(\chi^U)$	$log(\chi^V)$
$\tau_j^{BTA} \times \mathbb{1}\{y=2000\}$ (2-digit)	-0.099	-0.218	-0.033	-0.051	0.035	0.061	0.073	0.124
	(0.094)	(0.133)	(0.078)	(0.110)	(0.078)	(0.073)	(0.075)	(0.108)
$\tau_j^{BTA} \times \mathbb{1}\{y=2002\}$ (2-digit)	-0.050	-0.334***	-0.100*	-0.295***	-0.058	0.005	0.032	0.287***
	(0.063)	(0.100)	(0.054)	(0.081)	(0.070)	(0.073)	(0.073)	(0.094)
$\tau_j^{BTA} \times \mathbb{1}\{y=2003\}$ (2-digit)	-0.134**	-0.379***	-0.025	-0.454***	-0.051	0.075	-0.025	0.514***
	(0.063)	(0.088)	(0.059)	(0.083)	(0.066)	(0.066)	(0.076)	(0.102)
$\tau_j^{BTA} \times \mathbb{1}\{y=2004\}$ (2-digit)	-0.105*	-0.324***	0.121*	-0.412***	-0.057	0.093	-0.203*	0.473***
	(0.055)	(0.109)	(0.071)	(0.077)	(0.069)	(0.066)	(0.104)	(0.091)
$\tau_j^{BTA} \times \mathbb{1}\{y=2005\}$ (2-digit)	-0.096*	-0.230***	0.195***	-0.326***	0.095*	0.172***	-0.114	0.492***
	(0.057)	(0.086)	(0.067)	(0.064)	(0.055)	(0.062)	(0.076)	(0.080)
$\tau_j^{BTA} \times \mathbb{1}\{y=2006\}$ (2-digit)	-0.146**	-0.308***	0.050	-0.237***	0.055	0.197***	-0.015	0.421***
	(0.065)	(0.091)	(0.055)	(0.067)	(0.060)	(0.061)	(0.065)	(0.079)
$\tau_j^{BTA} \times \mathbb{1}\{y=2007\}$ (2-digit)	-0.143**	-0.296***	-0.004	-0.163*	-0.055	0.107*	-0.053	0.289***
	(0.066)	(0.088)	(0.093)	(0.083)	(0.067)	(0.065)	(0.094)	(0.095)
$\tau_j^{BTA} \times \mathbb{1}\{y=2008\}$ (2-digit)	-0.147**	-0.274***	-0.063	-0.292***	0.010	0.195***	0.064	0.485***
	(0.067)	(0.092)	(0.098)	(0.064)	(0.068)	(0.067)	(0.122)	(0.080)
$\tau_j^{BTA} \times \mathbb{1}\{y=2009\}$ (2-digit)	-0.122	-0.195*	0.176**	-0.193***	0.043	0.223***	-0.148*	0.409***
	(0.082)	(0.106)	(0.071)	(0.072)	(0.081)	(0.082)	(0.086)	(0.089)
$\tau_j^{BTA} \times \mathbb{1}\{y=2010\}$ (2-digit)	-0.224***	-0.233*	0.186*	-0.282**	0.059	0.269***	-0.148	0.536***
	(0.085)	(0.120)	(0.101)	(0.109)	(0.079)	(0.077)	(0.121)	(0.138)
Observations	125,577	125,577	125,558	125,574	121,348	113,978	121,329	113,975
R-squared	0.889	0.927	0.718	0.731	0.759	0.784	0.637	0.731
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Two-way								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

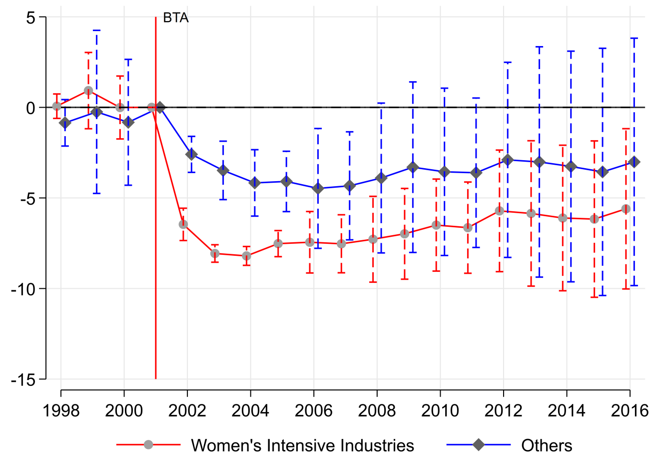
Notes: The table reports the results of regression equation (29) with separate dependent variables for manufacturing men (U) and women (V). Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** p<0.01, ** p<0.05, * p<0.1).

the BTA has led to a significant decline in the labor market distortion for women while the effect on men is mostly insignificant. There also appears to be no pretrend on these firm-level outcomes. Overall, the extended regression results provide strong evidence that the decrease in labor market distortion is largely driven by the impact of the BTA on women's labor market (relative to men's). This finding is consistent with the prediction of our theory and it underscores the differential effects of the BTA along the gender dimension in Vietnam's labor market.

8 Some Mechanisms

Having investigated the effect of BTA on labor market distortion and the effects separately for manufacturing men and women, the next natural question is about the practical mechanisms through

Figure 4: Vietnam's Manufacturing Exports to the US from 1998-2016 following the BTA: Heterogeneous Effects



Notes: The figure plots the BTA shock's heterogeneous effects on Vietnam's manufacturing exports to the US at 10-digit product levels across years. The effects are obtained from the regression $\ln(Exports)_{ht} = \sum_{y=1998,y\neq 2001}^{2016} \theta_y \mathbb{1}\{y=t\} \times \tau_j^{BTA-gap} + \sum_{y=1998,y\neq 2001}^{2016} \theta_y \mathbb{1}\{y=t\} \times \tau_j^{BTA-gap} \times \mathbb{1}\{WomenCA\} + \lambda_h + \lambda_t + \varepsilon_{ht}$, where h is the HS 10-digit level product category and $\tau_j^{BTA-gap}$ is the BTA tariff change measured at 2-digit industry level. The confidence intervals are 90%. The graphs are based on the authors' calculations with the trade data from the US Census.

which these effects might be taking place. Answers to this question can shed light on the theory and have policy implications that might not just be specific to the BTA. Differential effects along dimensions of firm ownership and gender above, combined with our model and the body of literature studying the impact of BTA on Vietnam's labor market, provide some leads, although they are neither mutually exclusive nor exhaustive.

Industries where Women Have A Comparative Advantage

We first examine whether the overall effect of the BTA on labor market distortion is driven by some specific industries where women might have a comparative advantage. We define an industry where women have a comparative advantage as one in which women's employment share was at least 70% in 2000 (pre-BTA). Indeed, there are precisely three 2-digit industries where this is the case: textile (17), fur (18), and leather (19). We interact the indicator for these industries with the BTA tariff reduction and investigate the possible heterogeneous effects of BTA on product-level exports and firm-level outcomes.

As shown in Figure 4, the BTA has indeed induced heterogeneous effects on the export of

Table 9: Impact of BTA on Firm-level Outcomes: By Industry with Women's Comparative Advantage

Dependent Variables	(1) $log(L)$	(2) $log(W)$	(3) $log(MRPL)$	(4) $log(\chi)$
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.211***	-0.064	0.073	0.116**
	(0.066)	(0.040)	(0.046)	(0.057)
$\tau_j^{BTA} \times PostBTA \times \mathbb{1}\{WomenCA\}$ (2-digit)	0.016	-0.016	-0.026	-0.006
	(0.063)	(0.041)	(0.049)	(0.043)
Observations	128,406	128,406	118,437	118,437
R-squared	0.911	0.725	0.711	0.609
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes

Notes: The table reports the results of regression equation (27) with four dependent variables: (1) log of employment, (2) log wage, (3) log of MRPL, and (4) log of measured distortion, but add an interaction term with the indicator for women's comparative advantage industries. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** p<0.01, ** p<0.05, * p<0.1).

manufacturing goods from Vietnam to the US. In particular, products belonging to industries where women have a comparative advantage have seen more significant growth following the BTA for the same level of tariff change, and this is especially true four years after the BTA (up until 2005). The magnitude of the difference in elasticity can be as large as 5 log points. This difference persists but is not statistically distinguishable from zero after 2005.

Despite heterogeneous effects on exports, the effects of BTA on firm-level outcomes spread out across all industries rather than concentrating on just a few industries where women have a comparative advantage. These results are shown in Table 9. Here, we find that the effects are of similar magnitude for all industries (i.e., the coefficients on the interaction terms are small and insignificant), suggesting that women's comparative advantage in specific industries is not what is driving the results on firms' outcomes in the labor market. Our results are robust to using alternative thresholds for women's comparative advantage, for example, at 50%.

Entry of FDI Firms following the BTA

Last but not least, we investigate whether controlling for FDI share at the industry level would absorb the effect of BTA on firm-level outcomes regarding their behavior in the labor market.

Table 10: Impact of BTA on Firm-level Outcomes: Controlling for FDI Penetration Share

Dependent Variables	(1) $log(L)$	(2) $log(W)$	(3) $log(MRPL)$	(4) $log(\chi)$
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.108*	-0.052	0.015	0.049
	(0.058)	(0.040)	(0.050)	(0.050)
FDI Employment Share (2-digit)	0.224***	0.053*	-0.101***	-0.153***
	(0.055)	(0.030)	(0.036)	(0.043)
Observations	128,406	128,406	118,437	118,437
R-squared	0.911	0.725	0.711	0.609
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes

Notes: The table reports the results of regression equation (27) with four dependent variables: (1) log of employment, (2) log wage, (3) log of MRPL, and (4) log of measured distortion. Standard errors in parentheses are clustered two-way at firm and industry-by-year level (*** p<0.01, ** p<0.05, * p<0.1).

This can shed important insights because we know from above that most of the effects of BTA on within-firm changes concentrate on domestic private firms rather than FDI firms or SOE firms. On the other hand, McCaig, Pavcnik and Wong (2022) find that BTA induces a significant increase in entry and share of FDI employment at the industry level and has a similar entry effect for domestic private PRI firms (although the private firms' employment share declines). Notably, employment at entry of FDI firms is often larger than that of average domestic firms. Such entry of large FDI firms plausibly constitutes a sizeable competitive shock in the local labor markets. We show the results, controlling for industry-level FDI share, in Table 10.

We find that the penetration of FDI following the BTA indeed absorbs almost all of the BTA's effects on firms' behavior in the labor market. In particular, a large part of the effect on employment and almost all the effects on wage, MRPL, and distortion are correlated with the industry's FDI employment share following the BTA. This result has two interesting implications. Although FDI firms do not adjust their behavior by themselves following the BTA and after partialling out the firm-level fixed effects (at least in the 2000-2010 period), their presence induces changes in the behavior of domestic firms in the labor market. These results are consistent with the hypothesis that the entry of large firms would induce competitive pressure that reduces distortion in the local labor market, forcing firms to increase employment and wages for local workers. Second, the fact that the reduction in distortion is driven by decreasing distortion for women suggests that entry of FDI firms particularly creates more competitive pressure on how domestic firms behave with respect to women. These results resonate with the findings in the literature that find more equal employment practices and better norms for women in FDI firms (see for examples Kodama, Javorcik and Abe (2018), Tang and Zhang (2021), Choi and Greaney (2022), Fang, Shams and Xu (2019)).

9 Concluding Remarks

In this paper, we study the impact of the expansion of export market access created by the US-Vietnam Bilateral Trade Agreement (BTA) on competition among manufacturing firms in Vietnam's local labor markets. We measure firm-level labor market power (distortion) using Vietnamese data from 2000-2010 and find that labor-market distortion is substantial and pervasive: a worker gets paid only about 59% of her (his) MRPL at the median firm. This result is in line with previous estimates for developing countries (e.g., Amodio and de Roux (2021) for Columbia, Pham (2020) for China, and most recently Amodio et al. (2024) for 82 low and middle-income countries). We find that the BTA permanently decreases the labor market distortion in manufacturing by 3.4%, and the effect concentrates on domestic private firms with the magnitude of 4.9%. In addition, when considering men and women separately, we find the distortion for manufacturing women is substantially higher and that the BTA-associated decline in the overall labor market distortion is primarily driven by the decline in distortion for women, amounting to more than 12%, highlighting a substantial effect of trade on gender inequality and misallocation working through the labor market competition channel. The entry of FDI firms combined with differential aggregate labor supply elasticities can explain these results.

Several questions remain open for future research. First, we only estimate the change in the level of the distortions but have yet to say anything about their aggregate misallocation. Quantifying the aggregate welfare gains from our results is important for future work. Second, it is possible to explore further the mechanisms through which trade affects labor market distortions and work for men and women, as well as the spillover effects to other formal sectors outside of manufacturing. Dissecting such mechanisms and spillovers will have important implications for theory and trade policy formulation in developing countries.

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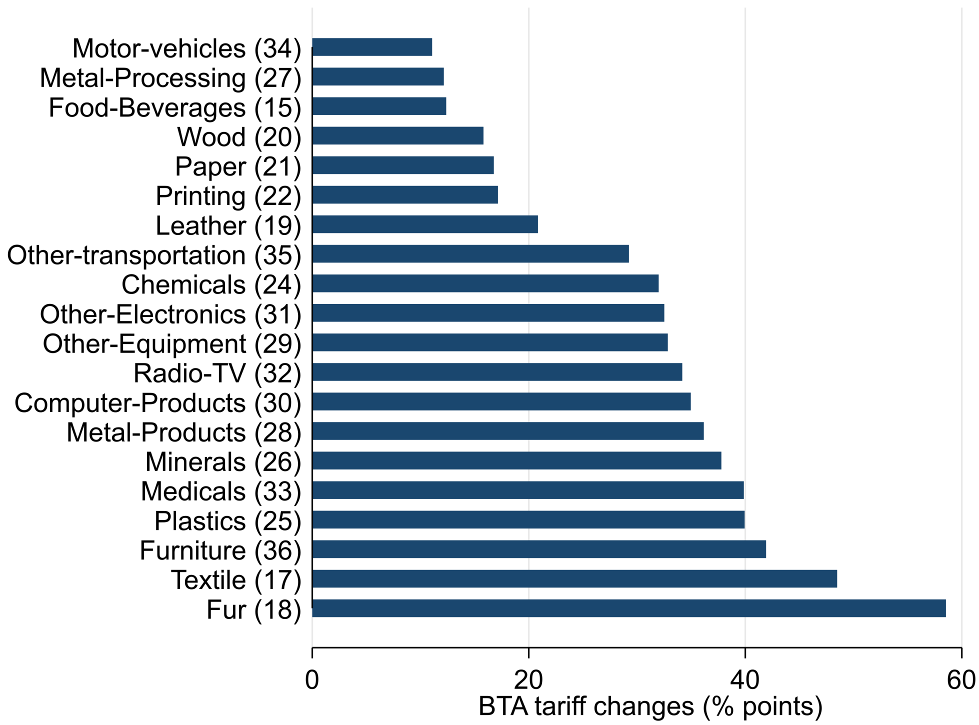
Appendix

A Data Appendix

A.1 BTA Tariff Changes

Figure A1: BTA Tariff Reductions across 2-digit Industries in 2001



Notes: The figure illustrates the tariff reductions across 2-digit manufacturing industries following the United States-Vietnam Bilateral Trade Agreement (BTA) in December 2001.

A.2 Vietnam Enterprise Survey

As described in Section 4, we use the Vietnam Enterprise Survey (VES) data for 2000-2010 collected by Vietnam's General Statistics Office (GSO). McCaig, Pavcnik and Wong (2022) provides an additional description of the Vietnam Enterprise Survey (VES) data. This appendix describes the data filtering process used for our analysis. We require data on key variables, including revenue, capital stocks (fixed assets), employment (total, men, and women), material expenditure, and total labor compensation (sum of wage bills, social insurance, and other payments). In addition, we need consistent industry and province codes. Reported Firm IDs (and, in some cases, Tax IDs) are used to identify and match firms over time. Firms matching in VES are straightforward and quite reliable in most cases, except for a small number of firms between 2000-2001, as reported in McCaig, Pavcnik and Wong (2022), which we handle with some robustness checks (we rerun the whole estimation procedures and regressions using data only from 2001-2010 and report the main results in Table B1). While all firms with more than 10 employees are required to register and fill out the survey by law, firms with less than 10 employees have options to operate as a formal enterprise or a household business. Firms below this size threshold are also surveyed based on a sampling approach that is not consistent across years. For this reason, we only keep firms with average employment greater than 10 to keep the sample consistent.[30]

Data Cleaning

We apply the following procedures in sequence from the raw panel data for all formal firms in the economy from 2000 to 2010. The manufacturing panel is then split from the overall sample based on raw 2-digit industry codes. The raw (unbalanced) sample includes $1,460,999$ firm-year observations, with $475,822$ firms spanning over 11 years.

- Drop if missing or negative values of revenue, capital stocks, employment, material expenditure, and total labor compensation. This procedure drops $429,525$ firm-year observations (about 29% of raw data), with most missing observations in capital and material.
- Drop if women's employment share is missing or outside range $[0,1]$. Drop if the material share of total revenue and labor compensation share of total revenue is missing or outside the $(0,1)$ range. This procedure drops $76,828$ firm-year observations (another 5% of raw data).
- Drop if missing information about industry and province (dropped $1,599$ observations).
- Drop observations outside the 0.1 and 99.9 percentile of revenue, capital stocks, employment, materials expenditure, and labor compensation. This procedure drops $85,977$ firm-year observations (another 6% of raw data).

[30] In 2010 and afterward, the size threshold changed slightly from 10 to 20 employees, 30 for some provinces and 50 for Hanoi and HCM city. We find robust results in our analysis with these alternative thresholds.

- Drop firms with average employment across years less or equal to 10 employees to keep a consistent size threshold. This procedure drops 503,436 firm-year observations (another 34% of raw data).

- Split the manufacturing panel. This panel includes 143,227 firm-year observations, with 38,843 firms spanning over 11 years.

- Drop firms in industry 16 (tobacco), 23 (nuclear), 30 (other computer products) and firms in province 207 (Bac Kan), 301 (Lai Chau/Dien Bien), 303 (Son La) due to few observations (dropped 943 observations in total).

The cleaned manufacturing panel includes 142,284 firm-year observations, with 38,581 firms spanning over 11 years. The cleaned non-manufacturing panel includes 298,834 firm-year observations, with 89,341 firms spanning over 11 years.

Construction of Variables

Our analysis requires data on key variables, including revenue, capital stocks, employment, material expenditure, and labor compensation. We implement the construction of each of these variables as below. In these constructions, we also use the consumer price index (CPI) series reported by the World Bank.[31]

- Revenue: Raw revenue from the data is deflated by the CPI series and measured in 2000 prices.

- Capital: VES report three data points related to fixed assets: (1) reported fixed assets, (2) fixed assets in original prices, and (3) accumulated depreciation. Each of these data points is reported twice in VES, in the beginning- and end-year values. In the data, the reported fixed assets (1) equals the corresponding fixed assets in original prices (2) minus the accumulated depreciation (3). Because of the lack of reliable capital price series and information on years when firms established are unreliable, we measure the real value of fixed assets by constructing a series of aggregate capital deflators.

[31] The CPI series for Vietnam can be retrieved at https://data.worldbank.org/indicator/FP.CPI.TOTL?end=2022&locations=VN&start=1995&view=chart.

We first use the reported fixed assets (net of depreciation) at the beginning and end of the year t to calculate the aggregate net nominal (current prices) investment in year t. We then deflate this nominal investment using the output deflators. This gives us a measure of real net investment in year t. The real aggregate capital stocks in year t_0 equals capital stocks at the beginning of year t_0 plus the real net investment in t_0. The real aggregate capital stocks in year t_0+1 equals the real aggregate capital stocks in year t_0 plus the real net investment in t_0+1, and so on. After calculating the real aggregate capital stocks, we take the ratio between the nominal end-year reported capital and its corresponding real value to compute a common capital deflator series for all firms. Our final firm-level capital stocks variable is computed by taking the average of beginning- and end-year reported fixed assets and deflating this average by the aggregate capital deflators.[32]

- Employment: VES report total employment, number of men and women in the total employment. Each of these variables is also reported twice, in the beginning- and end-year values. We compute the averages of reported employment at the beginning and end of the year.[33]

- Labor Compensation: We compute total labor compensation as the sum of wage bills, social insurance, and other payments to workers. We compute average "wages" as the ratio of total labor compensation and employment. The real values for labor compensation and wages are deflated by the output deflators.

- Material: Material expenditure is not directly available in the data. We compute the material expenditure based on the following accounting identity (in current prices):

$$material = revenue - gross\ profit - depreciation - labor\ compensation \tag{A1}$$

  The real value of the material expenditure is deflated by the output deflators.

- Industry Codes: We use VSIC 1993 4-digit industry codes reported in the VES data (for the

[32] For beginning- and end-year values of capital variables in the data, about $40-50\%$ of firm panels have end values in year t perfectly matched with beginning values in year $t+1$. However, the mismatch is often within a relatively small margin of errors, indicating that this might be due to errors in reporting practices. We take the average of the beginning- and end-year values to alleviate this issue, similar to how we handle employment variables below.

[33] We note that the use of averages does not affect our analysis regarding the fact that firms can enter or exit the sample. The beginning- and end-year reported values are the same for firms that enter or exit in a certain year.

years 2008-2010, VES data also report the industry codes based on both VSIC 1993 and VSIC 2007). As explained in Section 4, some firms switch industry codes within a panel. We use 2-digit industry codes to match firms with BTA tariff data from McCaig and Pavcnik (2018) and Vietnam's tariff data from WITS. For some robustness checks, we either drop all firms that switch industries or use the initial industry affiliation.

- Province Codes: We create a concordance for province codes that contains 60 consistent provinces/central cities throughout our sample period. We call all of these location units as provinces.

Descriptive Statistics

Table A1: Descriptive Statistics for Manufacturing Firm-level Data by Year

	Firm Counts (Count)	Employment (Mean)	Share of Women (Mean)	Share of Women (Median)	No-Women Share (Firm Share)	No-Men Share (Firm Share)
2000	6,464	173.30	0.41	0.36	0.00	0.00
2001	7,550	167.07	0.39	0.35	0.00	0.00
2002	7,994	175.83	0.40	0.35	0.00	0.00
2003	9,055	165.55	0.40	0.34	0.01	0.00
2004	10,775	170.14	0.40	0.36	0.00	0.00
2005	12,290	161.77	0.40	0.35	0.01	0.00
2006	13,984	149.86	0.40	0.35	0.01	0.00
2007	15,638	146.21	0.40	0.36	0.01	0.00
2008	18,524	126.17	0.40	0.36	0.00	0.00
2009	19,196	124.58	0.40	0.36	0.00	0.00
2010	20,814	117.58	0.41	0.37	0.00	0.00

B Robustness to Using Instruments for Production Function Estimation, Alternative Data Filtering, and Controlling for Capital

In this appendix, we report results on several robustness checks to estimation methods and alternative data filtering procedures. These robustness checks include (1) using instruments for production function estimation, (2) dropping all firms switching 2-digit industries, (3) using the initial industry affiliation for firms switching 2-digit industries, (4) using data from 2001-2010 only, (5) using 4-digit BTA tariffs, and (6) controlling for firm-level capital. For brevity, we report the robustness for Table 4 for domestic private firms because this is where our main effect concentrates, as shown in Table 6. Results for state-owned or foreign-owned firms remain insignificant, although they drive the equivalent all-firms coefficients in Table 4 slightly noisier in some cases. Overall, our key results remain robust to these checks. We also find that all our other key results remain robust to these checks. Those additional results are available upon request.

In the top panel of Table B1, we re-estimate the production function in Section 5 using natural instruments available in the VES data and report the main regression results after this procedure. In particular, the Vietnam firm-level data provide the values of employment and capital stock at the beginning of period t. We use these data to instrument for the actual employment and capital stock values in period t in our GMM procedure (particularly equation (21)). We then use the measurement of this alternative estimation procedure for subsequent regressions. We note here that even though using lag instruments is valid in theory, as in production function estimation literature, the lag instruments do not work well in the GNR method unless one imposes functional forms on production function (as in Ackerberg, Caves and Frazer (2015)). The reason is that the GNR method uses nonparametric identification and exhausts variation in the lag instruments for approximation of lag productivity and auxiliary objects, thus making these instruments weak. The natural instrument in VES data is thus an advantage in checking whether the GNR method works well. Our results suggest that the GNR method works well whether or not instruments are used, resonating with the finding in de Roux et al. (2021).

In the second panel of Table B1, we drop all firms that switch 2-digit industries and replicate all analysis steps. By dropping these firms, we find that our key results remain robust, especially regarding the effect of BTA on our measured distortion. The effect on wages becomes stronger for this data sample, while the effect on employment becomes weaker.

In the third panel of Table B1, we use the initial industry affiliation to assign industry codes for firms that switch 2-digit industries and replicate all analysis steps. We also find that our key results remain robust regarding the effect of BTA on our measured distortion. We similarly find that the effect on wages becomes stronger for this data sample while the effect on employment becomes weaker.

In the fourth panel of Table B1, we use the data from 2001-2010 only (to avoid the matching issue for a small number of firms between 2000 and 2001) and replicate all analysis steps. We also find that our key results remain robust without using the data for the year 2000. However, in this case, we only have one year before the BTA (2001) and can not check for a pretrend.

In the fifth panel of Table B1, we run our BTA regressions using 4-digit BTA tariffs. Regression results at the 4-digit level are consistent with those at the 2-digit level, although the coefficient magnitudes are reduced by about half. The change in magnitude likely reflects that more variation at the 4-digit level (within 2-digit industries) is also used for identification. Since we do not make any assumption about labor mobility across 4-digit industries, we use 4-digit regressions as robustness checks rather than trying to interpret them.

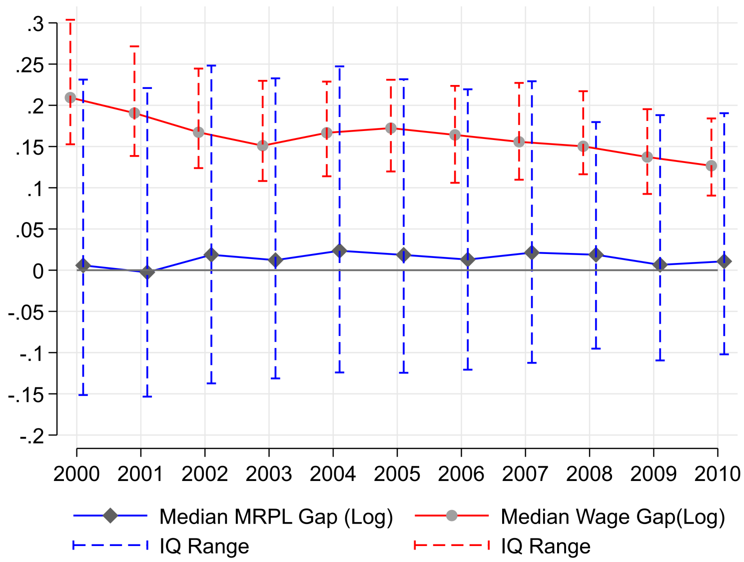
In the last panel of Table B1, we run our BTA regressions while controlling for firm-level capital accumulation. The goal is to check whether BTA works through the capital market to affect labor market distortion indirectly. We find little evidence of this channel: while firms with higher capital accumulation are positively correlated with the changes in employment, wage, MRPL, and distortion, controlling for firm-level capital accumulation almost doesn't materially alter the effect of BTA on labor market outcomes.

Table B1: Robustness of Results (Domestic Private Firms)

Dependent Variables	(1) $log(L)$	(2) $log(W)$	(3) $log(MRPL)$	(4) $log(\chi)$
(1) Using instruments for production function estimation				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.217***	-0.105**	0.116**	0.197***
	(0.069)	(0.045)	(0.053)	(0.050)
Observations	93,701	93,701	86,287	86,287
R-squared	0.861	0.667	0.665	0.588
(2) Drop all firms the switch 2-digit industries				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.101	-0.177**	0.017	0.165**
	(0.100)	(0.077)	(0.088)	(0.075)
Observations	77,092	77,092	70,897	70,897
R-squared	0.870	0.677	0.682	0.602
(3) Using the initial industry affiliation				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.036	-0.202***	-0.039	0.133**
	(0.096)	(0.073)	(0.076)	(0.061)
Observations	93,573	93,573	86,247	86,247
R-squared	0.860	0.667	0.670	0.590
(4) Using data from 2001-2010 only				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.256***	-0.078	0.107*	0.167***
	(0.072)	(0.053)	(0.056)	(0.053)
Observations	91,164	91,164	84,064	84,064
R-squared	0.865	0.666	0.669	0.589
(5) Using 4-digit BTA tariffs				
$\tau_j^{BTA} \times PostBTA$ (4-digit)	-0.124**	-0.061*	0.046	0.085**
	(0.049)	(0.035)	(0.036)	(0.038)
Observations	92,271	92,271	85,211	85,211
R-squared	0.870	0.670	0.674	0.591
(6) Controlling for firm-level capital				
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.248***	-0.115**	0.058	0.152***
	(0.059)	(0.045)	(0.049)	(0.046)
Log of Capital	0.210***	0.035***	0.154***	0.116***
	(0.005)	(0.003)	(0.004)	(0.005)
Observations	96,247	96,247	88,797	88,797
R-squared	0.882	0.670	0.695	0.601
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes

C Additional Figures and Tables

Figure C1: Firm-level MRPL and Wage Gap in Vietnamese Manufacturing from 2000-2010



Notes: The figure illustrates the firm-level gender MRPL and wage gap estimate for each year from 2000-2010 in Vietnamese Manufacturing using the approach described in section 5.

Table C1: (Robustness Checks) Impact of BTA on Local Entry, Exit, and Labor Market Share (2-digit) using PPML Regressions

	(1)	(2)	(3)	(4)
	PPML	PPML	PPML	PPML
Dependent Variables in Levels	Entry Counts	Exit Counts	Firm Counts	HHI (Wage-bill)
(Sample Used)	(2001-2010)	(2000-2009)	(2000-2010)	(2000-2010)
$\tau_j^{BTA} \times PostBTA$ (2-digit)	-0.890***	-0.502*	-0.495***	0.504***
	(0.333)	(0.301)	(0.149)	(0.097)
Observations	5,995	5,704	7,881	7,881
Market (jp) FE	Yes	Yes	Yes	Yes
Province-Year (pt) FE	Yes	Yes	Yes	Yes

Notes: The table reports the results on the effects BTA on local firm entry, exit, counts and wage-bill Herfindahl-Hirschman Index (HHI) using Poisson pseudo-maximum likelihood (PPML). Standard errors are clustered at market (2-digit) industry-by-province level (*** p<0.01, ** p<0.05, * p<0.1).