# The Effect of Export Market Access on Labor Market Distortion: Evidence from Vietnam*

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**Abstract**

This paper examines the effect of an export shock on the firm-level labor market distortion. Using Vietnamese firm-level data from 2000 to 2010 and a nonparametric production function approach, we measure firm-level distortionary wedges between equilibrium marginal revenue products of labor (MRPL) and wages. We find substantial wedges between equilibrium MRPL and wages, suggesting that the median manufacturing firm pays workers roughly 59% of their MRPL. Following the US-Vietnam Bilateral Trade Agreement (BTA), which significantly reduced US tariffs for Vietnamese manufacturers, firms in industries exposed more to the tariff reductions saw faster employment growth and faster declines in their MRPL-wage distortionary wedge. We find that the BTA permanently decreases our measured labor market distortion in manufacturing by 3.4%. We further exploit detailed information on gender composition to measure the MRPL-wage wedges separately for Vietnamese manufacturing men and women. We find that the median distortion is 26% higher for women relative to men, and the declining distortion for women is the main force driving the reduction in overall labor market distortion attributable to the BTA. Entry of FDI firms following the BTA appears to explain these results.

Keywords: International Trade, Export Market Access, Labor Market Distortion, Labor Market Power, Oligopsony, Gender Inequality
JEL Codes: F13, F16, F66, J62

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# 1 Introduction

The past decades have witnessed increasing globalization, particularly the rapid expansion of international trade and global supply chains. Meanwhile, the decline of labor share in national output is observed in many developed and developing countries (Karabarbounis and Neiman, 2014). Some blame for such decline is placed on globalization, although it is unclear how and whether globalization is a key factor contributing to it (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 their 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.

Global trade has been shown to have had large effects on domestic labor market outcomes such as employment and wages in many countries (see for reviews Feenstra and Hanson (2001), Harrison, McLaren and McMillan (2011), Goldberg and Pavcnik (2016)). Surprisingly, however, only a few studies have 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), 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 (MacKenzie (2019), Pham (2020), Felix (2021)) in the labor market. In the latter case, where the labor market is oligopsonistic, it can be shown that trade endogenously affects domestic labor-market outcomes, including labor shares, through its impact on labor-market competition. Our study builds upon and further develops this recent literature.

In this paper, 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 then examine the impacts of an export shock on our measured distortion that captures the wedge between the equilibrium marginal revenue product of labor (MRPL) and the wage. Our measure of distortion, which is the ratio of MRPL to wage, is an inverse measure of labor share at the firm level, conditional on the price-to-marginal cost markup. 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 firm-level labor market distortion.

Our first two main findings are that (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; and (2) firms in industries exposed more to the US tariff reductions see relatively faster employment and wage growth, and a faster decline in their incurred labor market distortion (which is the wedge between the marginal revenue product of labor and the wage). In our analysis, we also provide evidence that correlates our measured distortion to firm total factor productivity, employment, women's share of employment, labor-market concentration and the nature of ownership of the firm (foreign, private or state).

In addition, a unique feature of Vietnamese firm-level data allows us to make further contributions. Vietnamese firm-level data contain consistent information on the gender composition of each firm's workforce. We exploit this information by extending our estimation procedure and measuring distortion separately for men and women in manufacturing. Two main findings emerge here. On measurement, we find that the overall median distortion is 26% (substantially) higher for women than men. Nonetheless, we find that the declining distortion for manufacturing women is the primary driver of the overall reduction of the labor-market distortion caused by the BTA. We investigate further to explain why the BTA has this larger effect on reducing firms' labor market power for women. We find that the entry of FDI firms following the BTA plays an important role in explaining our results, resonating with the findings in McCaig, Pavcnik and Wong (2022) that FDI firms play an important role in shaping employment composition and employment growth across Vietnam's manufacturing industries. Our results shed light on the labor market power mechanism through which trade affects labor market efficiency and gender inequality in a developing country. The difference here is that we account not only for the gender wage difference (as in traditional gender wage-gap regressions in the literature) but also how much of that can be attributed to differences in the marginal productivity of men versus women and to differences in the firm's labor market power in men and women's labor markets.

Our paper starts with a description of the US-Vietnam BTA that we use as our natural experiment and several empirical facts surrounding the BTA.

We then provide a simple model of trade and oligopsony that allows for endogenous entry and exit, closely related to Pham (2020), to bring out some predictions and motivate our empirical analysis. Starting from a model of only one kind of labor, we extend it to have two kinds of labor, men and women (which can display both some degree of complementarity as well as some degree of substitutability). Thus, we are able to make predictions about the differential impact of the BTA on men and women's labor-market distortions.

Two important insights we get from our model are (1) the lower the elasticity of labor supply for any type of labor, other things remaining equal, the higher is the labor-market distortion, measured as the ratio of marginal revenue product to wage; and (2) firm entry has larger negative effects on the distortion for the group of workers with the lower elasticity of labor supply.

Our empirical results, which show a greater labor-market distortion and its greater responsiveness to the BTA for women, indicate a lower labor supply elasticity for women relative to men in Vietnam's manufacturing sector. This is consistent with arguments made by Hsieh et al. (2019) about women in the US in 1960 and earlier, when they faced barriers to human capital accumulation, such as restrictions on their admissions to colleges or vocational training, in addition to social norms supporting their role as homemakers and possible labor market discrimination. Recent work by Sharma (2023) estimates firm-level labor supply to be less elastic for women than for men in modern-day Brazil, 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 for female workers, and norms dictating what jobs are appropriate or not for women. These factors might lead to a lower labor supply elasticity for women. Dholakia (1987) has also argued in the case of India that the traditional family system (where the adult women have to carry the entire burden of tasks within their respective households) makes female labor supply more inelastic.

Following the theory section, subsequent sections of this paper respectively elaborate in depth on the data, measurement of our distortion of interest as well as its extension, and regression analyses, finally ending with our concluding remarks.

## 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 US and Vietnam starting 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 allowed Vietnam's exports immediate access to the US market. In exchange, Vietnam made extensive commitments in terms of changing its laws, regulations and administrative procedures that comply with international trade norms and standards. However, due to its status as a developing country, Vietnam's commitments are "phased-in", meaning that they are scheduled for implementation in a number of years following the BTA. Although Vietnam also committed to cut tariffs for 250 out of more than $6,000$ HS-6 US products, their own average tariff reductions were negligible since they had already applied low tariffs on their imports from the US prior the BTA.[1]

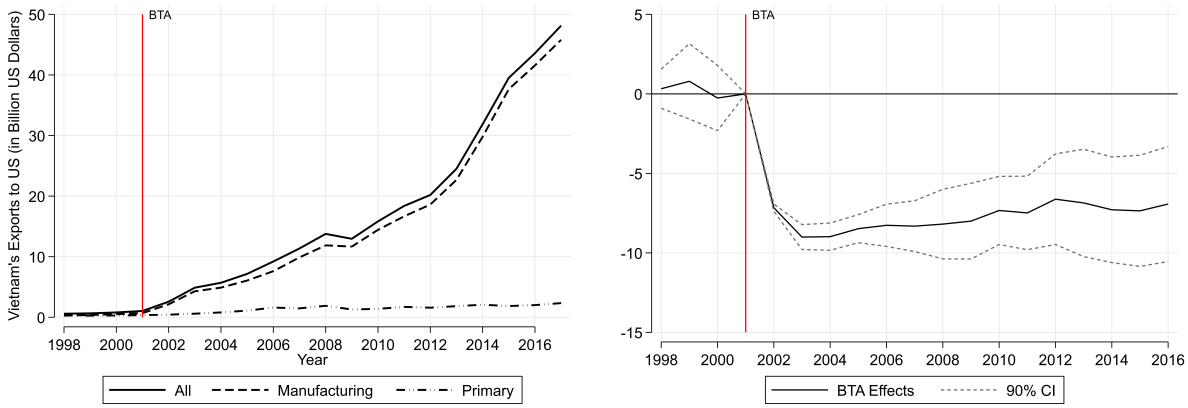
Upon being granted NTR/MFN status, Vietnam was moved from "Column 2" to "Column 1" (MFN) of the US tariff schedule. Importantly, although the BTA was subjected to a lengthy negotiation process on both sides, the magnitude of changes to US tariffs on imports of Vietnamese products was largely *predetermined* 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 determined through a multilateral bargaining process with other countries long before 2001.[2] 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).[3]

[1] 80% of these 250 tariff concessions were in the agriculture sector.

[2] Upon China's accession to the WTO in 2001, China was guarantee Column 1 tariffs, 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.

[3] More information about the BTA can be found in STAR-Vietnam (2003).

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 Exports Due to BTA

Notes: Panel (a) shows the value of Vietnam's exports to the US from 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 exports to US at 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.

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 level. The decrease is the largest for the manufacturing sector, from an average of 33.8% to 3.6%, and is much more modest for agriculture and other primary sectors. BTA tariff changes across 2-digit manufacturing industries are shown in Figure A1.[4] 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 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 to force, exports to the US grew to 2.6 billion US dollars, a 147% increase. This was a massive expansion of exports. By 2006, annual exports to the US amounted to 9.2 billion US dollars, a nine-fold increase, and

[4]Throughout our analyses, we use the BTA tariff data at the 2-digit industry level as the level of tariff shocks for reasons we will explain later, although our results are strongly robust to the BTA tariff data at the 4-digit industry level.

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.[5] Figure 1 also shows that the 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% prior to 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 level 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). $\lambda_h$ and $\lambda_t$ are product and year fixed effects, respectively. We plot the estimates of $\hat{\theta}_y$ in the panel (b) of Figure 1.[6] 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 were permanent and overall brought about a 180% increase in Vietnam's exports to the US by 2006. Our results from estimating equation (1) are strongly robust to using a PPML regression or using BTA tariff changes at more disaggregated levels.

## 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

[5] By this time, Vietnam was able to diversify its export portfolio, with the second- and third-largest export markets being China and Japan respectively.

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

firms are price takers in the goods market. We also assume that 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 the aggregate economy's outcomes can be easily inferred from the replicas of 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. 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 the local labor market and $\mathbb{L} = \sum_{i=1}^{N} L_i$ is the aggregate labor supply. Let $\bar{P} = \frac{1}{(1+\tau)}P$ denote the price in the goods market, and $\tau$ is the tariff that a foreign country imposes on domestic firms' goods. Firm $i$'s maximization problem is:

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

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

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

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

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 elasticity $\eta$ and the number of firms $N$. From the

FOC, the equilibrium employment can also be obtained as:

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

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, that equals $\frac{(PA)}{\chi}$, is increasing in firm productivity and the final-good price and decreasing in 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 $N^*$:

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

It also can be shown that $N^{*'}(\bar{P}) > 0$. The intuition is clear. 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 Human Capital Inputs: 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:

$$Q_i = A(\kappa L_{Ui}^{\frac{\sigma-1}{\sigma}} + (1-\kappa)L_{Vi}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}, \tag{9}$$

where the subscripts $U$ and $V$ denotes men and women 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:

$$W_U = B_U(\sum_{i=1}^{N} L_{Ui})^{\frac{1}{\eta_U}} \tag{10}$$

$$W_V = B_V(\sum_{i=1}^{N} L_{Vi})^{\frac{1}{\eta_V}} \tag{11}$$

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:

$$\begin{aligned}\max_{L_{Ui}, L_{Vi}} \pi = \bar{P}A(\kappa L_{Ui}^{\frac{\sigma-1}{\sigma}} + (1-\kappa)L_{Vi}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \\ - B_U(\sum_{i=1}^{N} L_{Ui})^{\frac{1}{\eta_U}} L_{Ui} - B_V(\sum_{i=1}^{N} L_{Vi})^{\frac{1}{\eta_V}} L_{Vi}.\end{aligned} \tag{12}$$

The FOC for $L_{Ui}$ and $L_{Vi}$ yields two conditions similar to equation (6):

$$\chi_U = \left(1 + \frac{1}{\eta_U N}\right) \tag{13}$$

$$\chi_V = \left(1 + \frac{1}{\eta_V N}\right). \tag{14}$$

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

$$\frac{\chi_U}{\chi_V} = \frac{\left(1 + \frac{1}{\eta_U N}\right)}{\left(1 + \frac{1}{\eta_V N}\right)} \tag{15}$$

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

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 but filing taxes separately are treated as distinct business entities. We treat these business entities as firms. All these firms or business entities are required to 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. In manufacturing, the cleaned unbalanced panel 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.[7] 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.[8] Appendix A.2 details our data filtering process. Table 1 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 1.5 times 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 at 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 the gender composition for each cell, using the variation in gender composition to predict the premium paid to men over women in each local labor market at each point in time.

Our BTA tariff data are obtained from McCaig and Pavcnik (2018) and McCaig, Pavcnik and

[7]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.

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

Table 1: Descriptive Statistics for Manufacturing Firm-level Data by Year

| | No. of Firms | 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 |

Wong (2022).[9] 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 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. Figure A1 in the Appendix illustrates this variation across 2-digit industries. We also check the robustness of our analysis by dropping all firms that their 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.

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

# 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 $t$. $\omega_{it}$ measures the revenue productivity, i.e., revenue TFP, and $\varepsilon_t$ 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 $(k_{it}, l_{it}, m_{it}) \in \mathbb{R}^3_{++}$.

Some notes should be made here about why estimating a revenue production function as in equation (16) is a reasonable approach to measure labor market distortion. 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.[10]

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 (2021)). 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

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

BTA tariff in our data. Another assumption we need to make is that we need to assume that firms are small in the national 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 and would generally be needed in any form of production function estimation where quantity data is not observed.

We now briefly describe how we estimate 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.[11] Following GNR, in the first stage, we estimate the following share-regression using a nonlinear least-square (NLS) procedure:

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

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 $D^{\varepsilon}(k_{it}, l_{it}, m_{it})$:

[11] In this case, we assume that the market for material is relatively frictionless, and hence, 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 consistent. This approach is also used in other empirical work, for example, in Halpern, Koren and Szeidl (2015).

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

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 $\mu_{it}$ 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 $\mu_{it}$. 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 $\mu_{it}$ 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 $\tau_{it}^{BTA}$, 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 $\mu_{it}$. A unique feature of the Vietnamese firm-level data is that it provides the value of labor and capital stock at the beginning of period $t$.[12] 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 $\varepsilon_{it}$ is a random measurement error, and does not affect 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. 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:

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

where $u_{it}$ and $v_{it}$ are the natural logs of numbers of men and women that firm $i$ employs at time $t$.[13] 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.

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

[13] As shown in Table 1, there is a very small share of firms each year that employ no men or no women. 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.

**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 employment, the gender gap regression at the firm level is an analogy to the individual-level regression, 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 <u>each</u> 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 $\widehat{\left(\frac{W_{jt}^U}{W_{jt}^V} - 1\right)}$, we impute these wage premia for firms in corresponding cells and calculate the average wages firms pay to each group.

Some empirical notes about our gender gap estimation ought to be made here. First, firm and worker heterogeneity can certainly affect cross-section wage variation. For the regression version of 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).[14] 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

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

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 year before the BTA for our regression analyses and precisely estimate the gaps for most cells.[15] 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 because we always control for an extensive set of fixed effects. 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 2 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 $\chi$ estimated for Vietnam's entire manufacturing sector during our sample period is 1.70, implying that a worker gets 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 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.[16]

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 $log(\chi)$

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

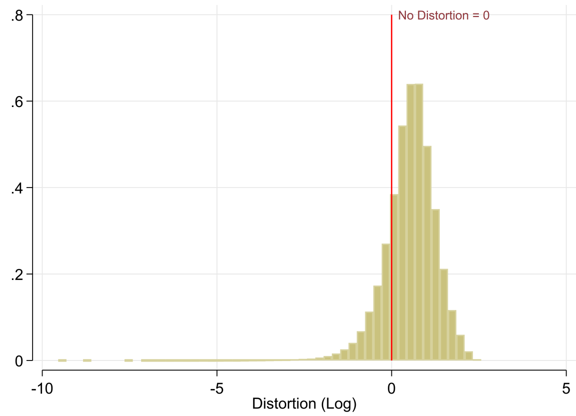
[16] Since there can be a certain amount of measurement errors coming out of our estimation procedure, we choose to interpret the medians of respective distributions, although we note that the mean values display almost similar magnitude and trends in all cases.

Table 2: Revenue Elasticities and Labor Market Distortion by Industry

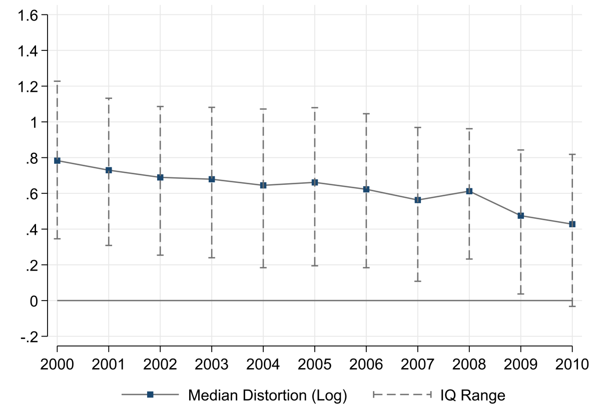
| Industry (2-digit) | Capital | Labor | Material | RTS | $\tilde{\chi}$ Mean | $\tilde{\chi}$ Median | No. Obs |
|---|---|---|---|---|---|---|---|
| 15.Food-Beverages | 0.07 | 0.22 | 0.76 | 1.05 | 1.44 | 2.07 | 21348 |
| 17.Textile | 0.08 | 0.27 | 0.70 | 1.04 | 2.21 | 1.98 | 6959 |
| 18.Fur | 0.12 | 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 |

Note: The table reports estimated statistics of the revenue elasticities of factors (capital, labor, material), the revenue return to scale (RTS), and the measured distortion ($\tilde{\chi}$) from production function estimation in Section 5. 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 $\chi$ outside the $1^{st}$ and $99^{th}$ percentiles each year. The last column reports the number of observations for each two-digit industry.

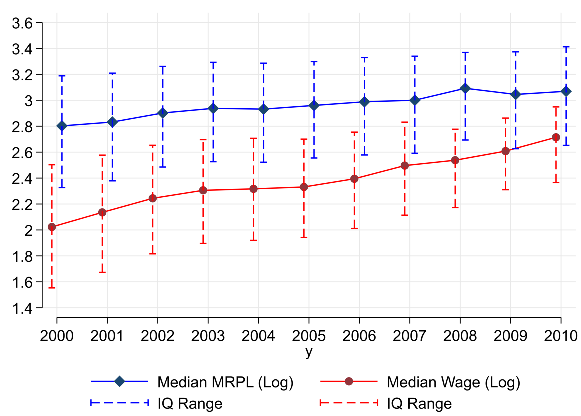
Figure 2: Distributions of Labor Market Distortions in Logs ($\log(\chi)$)




(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 ($\chi$), 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 $\chi$ 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).

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 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.[17] We 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. What is more interesting about this aggregate trend is 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 3 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.[18]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.[19] In economic terms, women get paid 52% of their MRPL while men get paid 68% of their MRPL at the respective median firms.

[17]This result resonates the findings in Pham (2020) for China's manufacturing sector. However, we do not find that the dispersion of the measured distortion decreased in Vietnam.

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

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

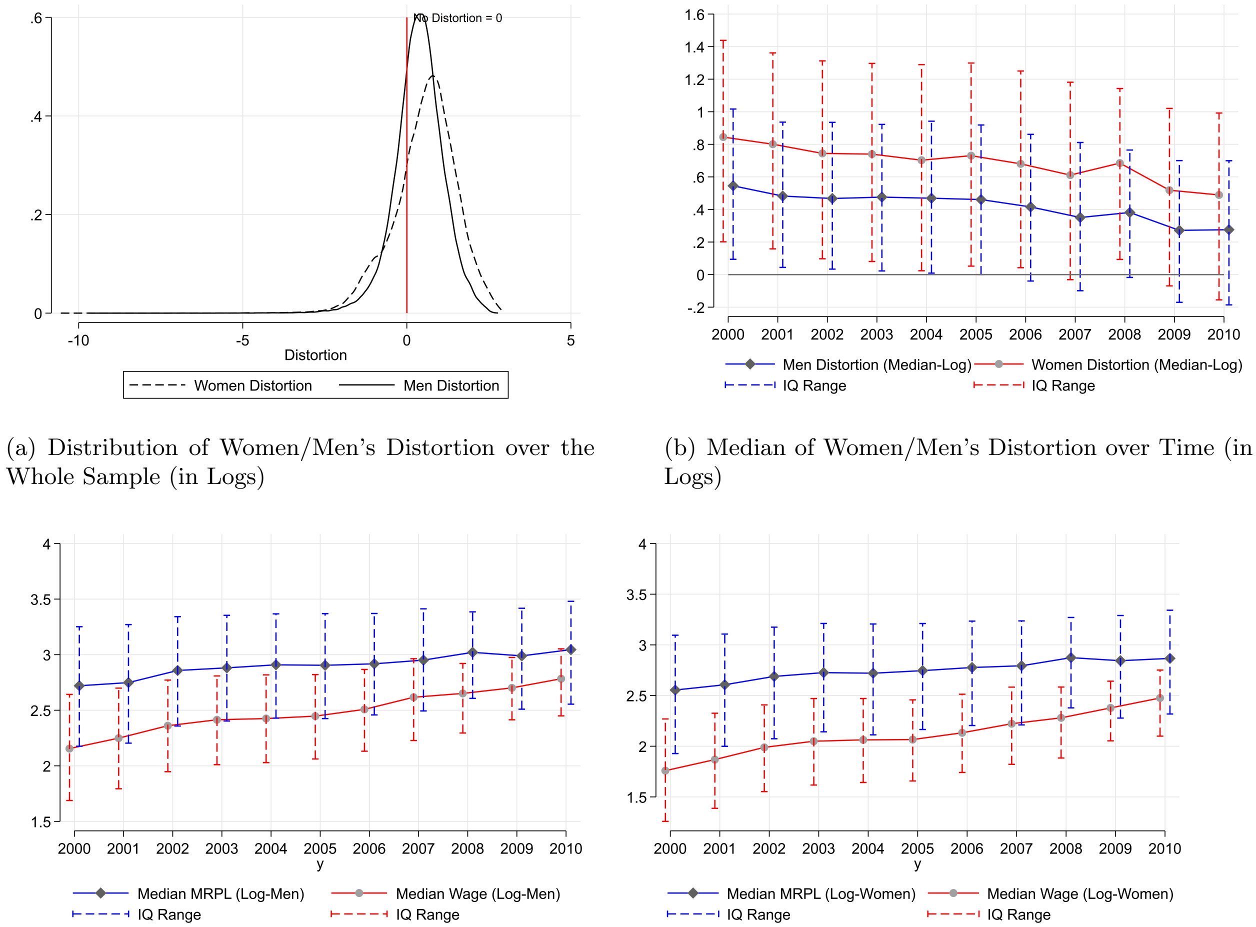
Table 3: Correlations between Measured Distortion and Firm Characteristics

| VARIABLES | (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 |

Note: The table reports the regression results of the measured distortion ($\chi_i$) 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).

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 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 F1 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 manufacturing men ($log(\chi^U)$) and women ($log(\chi^V)$) 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 $\chi^U$ and $\chi^V$ 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, $\tau_j^X$, 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. $\lambda_i$ controls for firms' fixed effects, and $\lambda_{pt}$ controls for province-by-year fixed effects. The coefficient of interest is $\theta$. Intuitively, $\theta$ 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.

### Local Entry, Exit, and Labor Market Share

To begin with our regression results, Table 4 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) log of average local labor market share. 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. We use PPML regressions for columns (1)-(3), although the linear OLS regression results are similar.

Columns (1)-(3) show that firm entry and firm counts across local labor markets respond to BTA tariff changes. In particular, BTA tariff reductions lead to increases in incidents of firm entry within a local labor market. The BTA tariff reductions also appear to have an effect on increasing

Table 4: Impact of BTA on Local Entry, Exit, and Labor Market Share (2-digit)

| | (1) PPML | (2) PPML | (3) PPML | (4) OLS |
|---|---|---|---|---|
| Dependent Variables | Entry Counts | Exit Counts | Firm Counts | Average Labor Market Share |
| Sample Used | (2001-2010) | (2000-2009) | (2000-2010) | (2000-2010) |
| $\tau_j^{BTA} \times PostBTA$ (2-digit) | -0.489*** | -0.260** | -0.457*** | 0.153*** |
| | (0.162) | (0.107) | (0.101) | (0.059) |
| Observations | 7,244 | 7,055 | 7,881 | 7,881 |
| R-squared | 0.794 | 0.778 | 0.951 | 0.807 |
| Market ($jp$) FE | Yes | Yes | Yes | Yes |
| Province-Year ($pt$) FE | Yes | Yes | Yes | Yes |

Note: The table reports the results on the effects BTA on local firm entry, exit, counts and average labor market share. Standard errors are clustered at market (2-digit) industry-by-province level (*** p<0.01, ** p<0.05, * p<0.1).

incidents of firm exit. 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 compute the average local labor market share for each market ($jp$) and regress this average share on the BTA shock in column (4). As a matter of fact, the increase in number of firms due to the BTA translates to a decrease in the average firm's local labor market within each market. When we regress the local labor market share on BTA tariff reductions at the firm level, we find a similar result: the BTA has led to a decrease in the firm's market share within each local labor market. These results resonate with the findings in the previous literature where plant survival rate, growth, and consequential labor market outcomes are associated with trade shocks (Bernard, Jensen and Schott (2006), Asquith et al. (2019)).

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

Table 5 reports the estimation 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. We decompose these overall effects in the dynamic regression results below. Columns (3)-(4) show the

Table 5: Impact of BTA on Firm-level Outcomes

| 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 |
| Location-Year FE | Yes | Yes | Yes | Yes |
| Clustered Two-way | | | | |
| *Firm* | Yes | Yes | Yes | Yes |
| *Industry-by-Year* | Yes | Yes | Yes | Yes |

Note: 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).

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 labor market distortions, 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 $30 \times 0.112 = 3.36$ percent due to the BTA based on a simple calculation.

To breakdown the response of firms' outcome variables overtime, we next estimate a dynamic version of our DID model as follow:

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

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 $\mathbb{1}\{y=t\}$.[20] Table 6 reports the estimation results.

Consistent with the results in Table 5, column (1) shows that employment growth is significantly

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

Table 6: Impact of BTA on Firm-level Outcomes (Dynamic DID)

| 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 |
| Location-Year FE | Yes | Yes | Yes | Yes |
| Clustered Two-way | | | | |
| *Firm* | Yes | Yes | Yes | Yes |
| *Industry-by-Year* | Yes | Yes | Yes | Yes |

Note: 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).

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 mostly statistically insignificant in subsequent years, implying 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 again 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 MRPL. These results are consistent with upward-sloping labor supply curves facing firms in the short run. Second, the results from columns (1) and (2) can be used as a reduced-form results validation for our production function measurement of distortion. 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 mean, or workers get paid 54% of MRPL at the average firm. The immediate responses regarding wage and employment to the BTA shock (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 is very close to our median or mean estimate based on production function estimation. Note, interestingly, that using our distortion formula from the theory and plugging the mean value of the calculated distortion for 2001 equal to 1.8, we get a firm-level labor supply elasticity of 1.2 (or a local labor market labor supply elasticity of 0.12), which is pretty close to the above calculation of 1.4. 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, no pre-trend pattern appears to exist for firm outcomes for any of the four columns, supporting our causal interpretation of the estimates.

### Effects for Manufacturing Men versus Women

Using our extended measurement results in Section 5, we 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 among 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 value. Columns (3)-(4) show the regression results for wages. Interestingly, while we do not see a significant relative wage growth for men, women's wage growth is significantly larger for firms in industries more exposed to the BTA. Columns (5)-(6) reveal that the decline in $MRPL$ is significant for women, 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 effectively imply that the overall reduction in labor market distortions shown in column (4) of Table 5 is mainly driven by decreased labor market distortions for manufacturing women, in which about 2/3 is from narrowing the wage gap, and 1/3 is from widening the 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 $30 \times 0.405 = 12.15$ percent due to the BTA. The overall decrease in distortion of 3.36 percent computed in the previous part is thus the net effect of two factors: (1) the increase in the share of manufacturing women following the BTA, which increases the average distortions (because the women's labor market is characterized by more distortions), and (2) the endogenous decrease in distortions in the women's labor market due 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 $MRPL$s for men do not respond to the BTA, while the $MRPL$ for women see slower relative growth in more BTA-exposed industries, especially in later years since 2005. Columns (7)-(8) further confirm the results in Table 7 in that the BTA has led to significant declines in labor market distortions for women, while the effects on men are 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 distortions is largely driven by the impact of the BTA on women's labor market (relative to men's). This finding is not only consistent with the prediction of our theory, but it also underscores the differential effects of the BTA along gender lines on Vietnam's labor market.

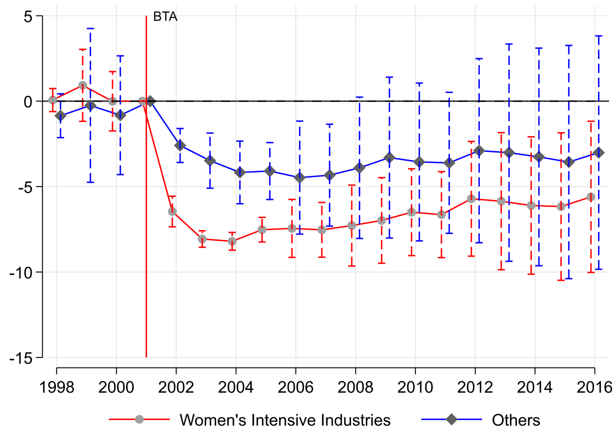
### Heterogeneous Effects and Foreign Direct Investment (FDI)

Having investigated the overall effect of BTA on labor market distortion and the effects separately for manufacturing men and women, the next natural question to ask is where these effects are coming from, especially regarding the practical working mechanisms of the BTA. Differential effects along the dimensions of men and women above, combined with the body of literature studying the impact of BTA on Vietnam's labor market, provide some clues. Given that the effect of BTA on distortion concentrates on manufacturing women, the distortion results may be driven exclusively by specific industries where women have a strong comparative advantage. In addition, recent work on trade and Vietnam's manufacturing sectors suggests that there might be different effects across firm types (Baccini, Impullitti and Malesky, 2019), or the significant entry of FDI following the BTA could drive the result (McCaig, Pavcnik and Wong, 2022). We investigate these practical mechanisms in this subsection.

We first check whether the overall effect 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 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 exports 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, 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 zeros in later years.

Despite heterogeneous effects on exports, the effects of BTA on firm-level outcomes spread out across industries rather than just concentrating on industries where women have a comparative advantage. These results are shown in Table 9. Here, the effects are almost the same for all industries, suggesting that women's comparative advantage in certain industries is not what is driving the results on firms' outcomes in the labor market. Our results are robust to using alternative

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




*Notes*: The figure plots the BTA shock's effects on Vietnam's US exports at 10-digit product levels across years. The effects are obtained from the regression $\ln(Exports)_{ht} = \sum_{y=1998,y\neq2001}^{2016} \theta_y \mathbb{1}\{y = t\} \times \tau_j^{BTA-gap} + \sum_{y=1998,y\neq2001}^{2016} \theta_y \mathbb{1}\{y = t\} \times \tau_j^{BTA-gap} \times \mathbb{1}\{WomenCA\} + \lambda_h + \lambda_t + \varepsilon_{ht}$, 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 graphs are based on the authors' calculations with the trade data from the US Census.

thresholds for women's comparative advantage, for example, at 50%.

Next, we investigate whether the effects of BTA on distortion vary by firm's ownership. We investigate the effects for three separate types of firms: State-Own Enterprises (SOE), Domestic-Private (PRI), and Foreign-Owned (FDI). The results are shown in Table 10. We find that almost all the effects come from domestic-private firms, with the coefficient estimates for this type of firm closely matching those in Table 5. 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 within the firm due to the BTA is 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 attributed to new FDI entries rather than continuing FDI firms. We find similar results here using a firm-level analysis.

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. This is important 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) finds 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 firms (although the private firms' employment share declines). Notably, employment at entry of FDI firms is often larger than that of average domestic firms and, in theory, constitutes a sizeable competitive shock in the local labor markets. We show the results, controlling for industry-level FDI share, in Table 11.

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 FDI penetration following the BTA. This result has an interesting implication. Although FDI firms do not adjust their behavior by themselves following the BTA (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 theoretical 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.

## 8 Concluding Remarks

In this paper, we study the impact of a large export expansion on the competition among firms in the Vietnamese labor market. We are able to measure labor market distortions using Vietnam's firm-level data for the period 2000-2010. We find that labor-market distortions are substantial and pervasive, suggesting that a worker gets paid only about 59% of his/her MRPL. This result is not very different from some previous estimates for developing countries (e.g., Amodio and de Roux (2021), Pham (2020)). We also find that the BTA has led to a significant decline in labor-market distortions characterizing manufacturing firms, with the overall decline being 3.36 percent. In addition, when considering men and women separately, we find the distortions for manufacturing women are substantially higher and that the BTA-led decline in overall labor market distortions is largely driven by the decline of distortions for women, amounting to 12.15%, highlighting a substantial effect of trade on gender inequality working through the labor market distortion channel.

Some issues are still left unexplored in our analyses. First, we only estimate the change in the level of the distortions but say nothing about misallocation, which can also further arise from the dispersion of the distortions. Thus, quantifying the aggregate welfare gains from our results is important for future work. Second, it is possible to explore further the mechanisms through which labor market distortion affects work for men and women and the spillovers to other formal sectors. We plan to address these issues in future research.

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

| | (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 |
| Location-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 |

Note: The table reports the results of regression equation (27) with separate dependent variables for manufacturing men and women. 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).

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

| Dependent Variables | (1) $log(U+1)$ | (2) $log(V+1)$ | (3) $log(W^U)$ | (4) $log(W^V)$ | (5) $log(MRPL^U)$ | (6) $log(MRPL^V)$ | (7) $log(\chi^U)$ | (8) $log(\chi^V)$ |
|---|---|---|---|---|---|---|---|---|
| $\tau_j^{BTA} \times \mathbb{1}\{y=2000\}$ (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 |
| Location-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 |

Note: The table reports the results of regression equation (29) with separate dependent variables for manufacturing men and women. 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).

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

| 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 |
| Location-Year FE | Yes | Yes | Yes | Yes |
| Clustered Two-way | | | | |
| *Firm* | Yes | Yes | Yes | Yes |
| *Industry-by-Year* | Yes | Yes | Yes | Yes |

Note: 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).

Table 10: Impact of BTA on Firm-level Outcomes: By Firm's Ownership Types

| 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 |
| Location-Year FE | Yes | Yes | Yes | Yes |
| Clustered Two-way | | | | |
| *Firm* | Yes | Yes | Yes | Yes |
| *Industry-by-Year* | Yes | Yes | Yes | Yes |

Note: 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).

Table 11: Impact of BTA on Firm-level Outcomes: Controlling for FDI Penetration Share

| VARIABLES | (1)<br>$log(L)$ | (2)<br>$log(W)$ | (3)<br>$log(MRPL)$ | (4)<br>$log(\chi)$ |
|---|---|---|---|---|
| $\tau_j^{BTA} \times PostBTA$ (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 |
| Location-Year FE | Yes | Yes | Yes | Yes |
| Clustered Two-way | | | | |
| *Firm* | Yes | Yes | Yes | Yes |
| *Industry-by-Year* | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: 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).

## References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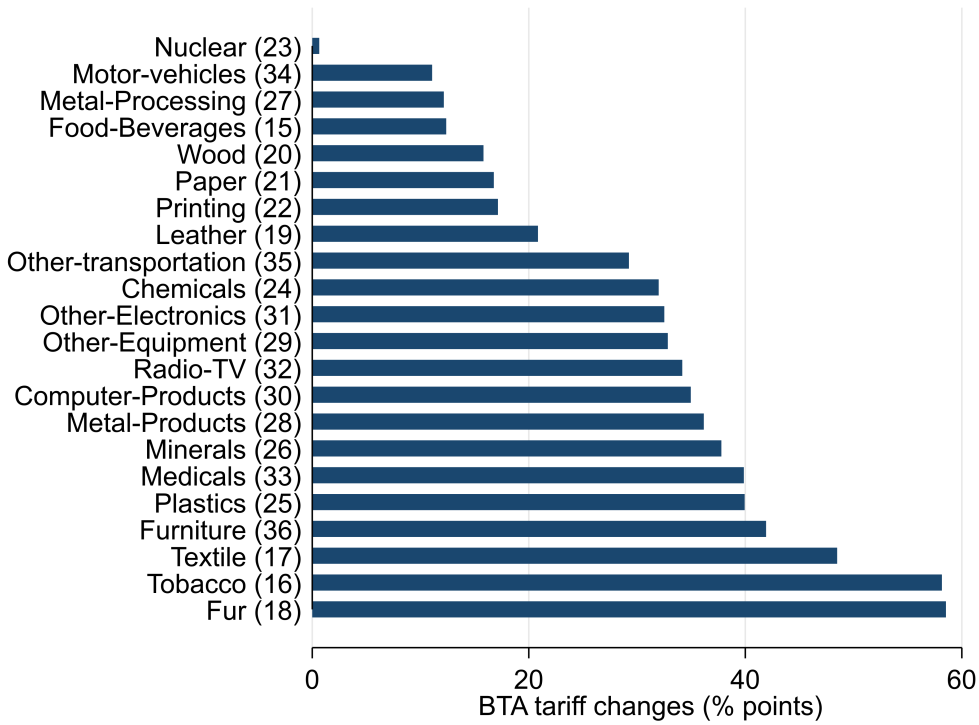
# Appendix

## A Data Appendix

### A.1 BTA Tariff Changes

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




<u>*Notes*</u>: 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. 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.[21]

### 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).

[21] 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 implement robustness checks in our analysis with these alternative thresholds and find robust results.

- 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.[22]

- 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.

[22] 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.[23]

- 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.[24]

- 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

[23] 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.

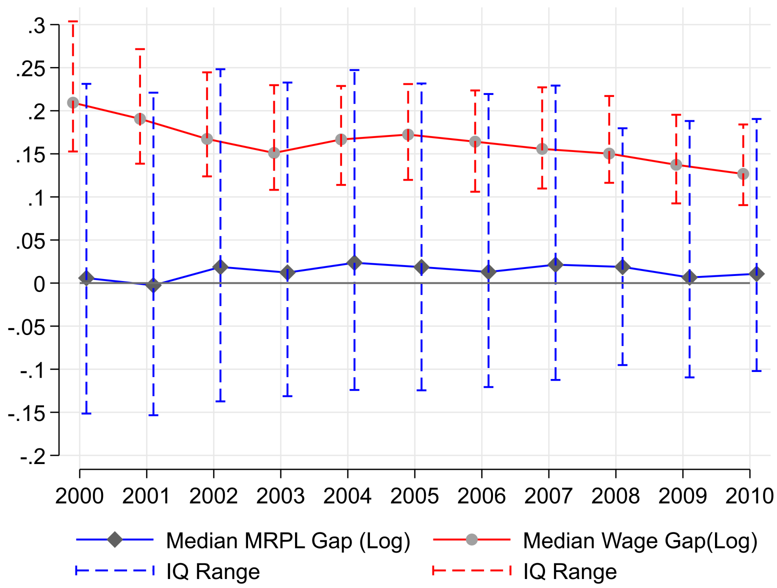
[24] We note that the use of averages does not affect our analysis regarding the fact that firms can enter or exit the sample. The beginning- and end-year reported values are the same for firms that enter or exit in a certain year.

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.

## B Additional Tables and Figures

Figure F1: 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.