ESSAYS ON GLOBALIZATION, LABOR MARKET, AND PRODUCTIVITY

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Abstract

This dissertation studies issues at the intersection of globalization, labor market, and productivity in developing countries. It is composed of three chapters.

Chapter 1 studies how a country’s trade policy affects competition in its domestic labor market. In a heterogeneous-firm model with oligopsonistic local labor markets, this chapter demonstrates that opening up to trade can affect distortions in such markets. These distortions arise because firms are large and able to exercise market power over their local workers. Using a panel dataset of Chinese manufacturing firms from 1998-2007, I measure firm-level labor market distortion, captured by the ratio between marginal revenue product of labor and wage, and examine its evolution following China’s trade policy reform in 2001. The baseline measure of the overall distortion implies a 53% pass-through rate of an idiosyncratic productivity shock to wage. The component of this distortion that arises purely from labor market power accounts for almost 80% of the overall distortion. I find that China’s trade policy reforms have led to a substantial net reduction in the labor market power distortion, with large effects working through the liberalization of input tariffs. These findings suggest novel effects of trade policy that deviate from the conventional trade models featuring perfect competition in the labor market.

Chapter 2 investigates the impact of a large export shock on intergenerational mobility in Vietnam. We use eight rounds of Vietnam Household Living Standards Surveys (VHLSSs) spanning over almost two decades to measure intergenerational mobility based on education levels of fathers and sons within households. Exploiting the US-Vietnam Bilateral Trade
Agreement (BTA) in 2001 as an export shock and a difference-in-difference research design, our analysis suggests that the BTA shock has led to substantial upward occupational mobility, accounting for one-third of overall increase in mobility in Vietnam during our sample period. We also show that this effect potentially works through improvements in educational attainment. The results further reveal that both increases in exports overall and export unit-value in particular have contributed to the upward mobility. Our results highlight that international trade as an external shock can break down the persistence of socioeconomic status across generations in Vietnam.

Chapter 3 examines two novel productivity effects of foreign ownership and foreign acquisitions on Chinese high-tech manufacturing firms: the dynamic and the non-(Hicks)-neutral effects. The dynamic productivity effect of foreign ownership arises because adoption of foreign technology and management practices often takes time to fully realize. On the other hand, since advanced production technologies tend to have non-neutral productivity implications in developed countries, meaning that they could be capital- or labor-augmenting, such technology, transferred through foreign investment, can have similar effects in developing countries. We propose an econometric framework to estimate both effects. Our framework extends a recent nonparametric productivity framework developed by Gandhi, Navarro, and Rivers (2017), in which identification is achieved by firm’s first-order condition and timing assumptions. We find strong evidence of both effects due to foreign ownership. These effects provide a more comprehensive perspective on the impact of foreign investment on firms’ productivity in developing countries.
ESSAYS ON GLOBALIZATION, LABOR MARKET, AND PRODUCTIVITY

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Chapter 1

International Trade and the Labor Market Power of Firms: Theory and Evidence

1.1 Introduction

The impact of international trade policy on labor market outcomes is a central topic in the international economics literature (Goldberg and Pavcnik (2016)). Although voluminous, the majority of empirical work has been based primarily on the theoretical premise that firms behave competitively in the labor market.\(^1\) This premise stands in stark contrast to a recent empirical labor economics literature which documents that firms possess some degree of market power in the labor market, and thus, can inflict distortionary effects on the economy by engaging in non-competitive conduct therein (see for examples Card et al. (2018), Berger, Herkenhoff and Mongey (2019)).\(^2\) Since labor market power is closely tied to

\(^1\)See for examples the canonical models of international trade with heterogeneous firms, such as those in Melitz (2003), Bernard et al. (2003), Melitz and Ottaviano (2008), and Atkeson and Burstein (2008).

\(^2\)Earlier discussions and empirical evidence on firms’ labor market power in the labor economics literature can be found in Boal and Ransom (1997), Manning (2003), Staiger, Spetz and Phibbs (2010), Ashenfelter, Farber and Ransom (2010), and Dube et al. (2018).
a firm’s performance, which is in turn affected by trade, this paper examines whether trade policy can affect competition in the labor market and thus, alter labor market outcomes through this channel.

Providing a compelling answer to this question is difficult for two reasons. First, from a theoretical point of view, it is not obvious how firms, playing the central role as mediators, transmit trade shocks in the product market to the labor market. In the presence of labor market imperfections, characterizing this transmission requires making explicit assumptions about competition structures in both the product and labor markets, the latter often missing in theoretical trade models. Second, from an empirical perspective, firms’ distortions in the labor market are not directly observable from data, and therefore, measuring the distortions requires a consistent methodology. This paper offers a novel approach to both of these problems and provides an estimate of the impact of trade policy on the labor market power of firms, using Chinese firm-level data, with China’s accession to the World Trade Organization (WTO) in 2001 as a historical policy experiment.

Formally, my analysis delivers three key contributions. I first develop a theoretical framework to formalize the notion of labor market distortion at the firm level and explain the mechanism through which trade policy affects firms’ competitive behavior in the labor market. A distinct feature of this theoretical framework is that it embeds a generic oligopsony competition structure in the labor market into a workhorse trade model with heterogeneous firms as in Melitz (2003), and allows entry and exit of firms to affect competition within a local labor market. Second, guided by the theory, I propose two complementary approaches to empirically measure labor market distortion at the firm level: (1) a production function estimation approach; and (2) a regression approach that exploits a unique exogenous demand shifter in China’s context, namely the US-China Trade Policy Uncertainty (TPU) shock. These two measures not only serve to cross-validate each other, but also help to quantify the magnitude of the distortion that is entirely caused by the labor market power of firms, relative to all other forms of distortion. Finally, using the resulting measures of labor
market distortion, I establish a causal link between China’s trade policy reform, specifically reductions in both output tariffs and input tariffs, and the consequential changes in labor market distortions.

To develop my results, I start off by deriving a “reduced-form” representation of the labor market distortion from a simple firm’s profit maximization problem, following the modeling convention in the misallocation literature (Hsieh and Klenow (2009), Liu (2019)). A key result from this representation is that all sources of distortion in the labor market can be nonparametrically summarized by the ratio between the equilibrium marginal revenue product of labor (MRPL) and wage (w) paid by the firm, which I henceforth refer to as the overall distortion. Since labor market distortion can arise due to a variety of sources, I decompose the overall distortion into two main components: the exogenous distortion versus the endogenous distortion. The exogenous distortion reflects the inefficient policy features of the labor market, such as labor regulations and institutional constraints, and generally does not respond to firm-level idiosyncratic shocks. On the other hand, the endogenous distortion arises due to firm’s labor market power, and thus can potentially be altered by trade shocks.

How does trade policy affect firms’ labor market power distortion? To answer this central question and provide theoretical guidance for my empirical analysis, I develop a tractable trade model with heterogeneous firms and oligopsonistic competition in the labor market.\(^3\) The model has two distinct features. First, firms are assumed to be atomistic and compete monopolistically within the national product market, as in Melitz (2003). Nonetheless, firms’ locations are distributed over a continuum of local labor markets, within which firms are large employers and employ only local workers. Within each local labor market, I explicitly model the oligopsony structure using a nested constant elasticity of substitution (CES) labor supply system, building on the recent microfoundations from the labor economics literature, particularly as in Berger, Herkenhoff and Mongey (2019). Second, I allow for entry and exit of firms following a sectoral trade shock, which consequently serves as the

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\(^3\)As will be shown later, the model shares similar flavors to trade models with oligopolistic competition in the product market, for example as in Atkeson and Burstein (2008) and Edmond, Midrigan and Xu (2015).
main mechanism through which trade policy affects the distortion in the labor market. This modeling approach is motivated by two robust empirical patterns that I observe in the data: (1) there are massive entries and exits following trade liberalization within a local labor market, and (2) firms’ local labor market share responds significantly to trade policy. To the best of my knowledge, this is the first trade model that incorporates endogenous entry and exit in an oligopsony context and allows them to affect labor market structure.

My model provides sharp and intuitive predictions for the impact of trade policy. To begin with, in this model, more productive firms always have larger local labor market shares and exercise more market power over their workers. Starting from an initial equilibrium, when the Home country opens up to trade by lowering its output tariffs, the competitive pressure from Foreign imports reduces each firm’s profit. Those firms at the margin, i.e. firms with productivity level near the operating threshold, reoptimize and decide to: (1) stay or (2) exit the market, whereas non-incumbent firms may decide to (3) enter. Since profit generally decreases due to competitive trade shocks, the least productive firms exit; labor market share is reallocated towards more productive firms; and thus, the average distortion increases. On the other hand, when the Home country lowers input tariffs, it reduces production cost for all firms that use foreign inputs, increases each firm’s profit, and induces entry of less productive firms into the market. As these firms gain market share, the average labor market distortion decreases.

Empirically, I tackle the measurement of the labor market distortion with two approaches. My baseline approach exploits the “reduced-form” representation to measure the overall distortion. More specifically, since the distortion can be captured by the ratio between the marginal revenue product of labor (MRPL) and wage (w) paid by the firm, measurement of the distortion translates naturally into estimation of MRPL, which can typically be obtained by identifying a revenue production function. To this end, I adopt a production function

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4Benmelech, Bergman and Kim (2018) document similar patterns for US manufacturing sectors. They find that employer concentration, measured by the Herfindahl-Hirschman Index, decreases substantially following the import competition shock from China in the early of the 2000s.
estimation technique recently introduced in the industrial organization literature by Gandhi, Navarro and Rivers (2017) (henceforth, GNR) to estimate a general, nonparametric production function using Chinese firm-level production data. The GNR method is distinguished from other existing methods, such as Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015), in that its identification is grounded in economic theory, rather than in functional-form assumptions of the production function.

In the second approach to measurement, I exploit a unique exogenous demand shock to Chinese firms, namely the US-China Trade Policy Uncertainty (TPU) shock, to identify the endogenous distortion. This approach combines the insights from the pass-through and trade policy uncertainty literatures, as in Amiti, Itskhoki and Konings (2018) and Handley and Limão (2017), Pierce and Schott (2016), respectively. The intuition for the identification is that the TPU shock technically acts as an exogenous labor demand shock. Therefore, by observing the response of firms in terms of wage and employment, I can trace out the slope and thus, elasticity of the labor supply curve. Furthermore, I allow for the pattern of the response to be dependent on firms’ local labor market share, which consequently permits a measure of share-dependent firm-level endogenous distortion computed from the regression estimates.

From the empirical estimates of the labor market distortion, two main findings emerge. First, the baseline estimates of the overall distortion from production function estimation indicate that labor market distortion is pervasive among the Chinese manufacturing sectors, with the average magnitude of the distortion implying a 53% pass-through rate of an idiosyncratic productivity shock to wage. The endogenous distortion, which arises due to firms’ labor market power, accounts for almost 80% of the overall distortion. Importantly, throughout my 10-year sample of Chinese firms, I also find that key moments such as the

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5Following China’s accession to WTO in 2001, the US moves China permanently from the “Column 2” tariffs to the Most Favored Nation (MFN) tariffs, and thus eliminates the possibility that China might face surprisingly high “Column 2” tariffs rather than the MFN tariffs, which are already granted to China prior to its WTO accession. It is also important to note that this TPU shock of US towards China is distinct and uncorrelated to China’s own trade policy, which is the main focus of this paper.

6This pass-through rate would be 100% in an environment where there is no labor market distortion.
mean, median, and dispersion of the distortion decrease over time.

With the obtained measures, I empirically assess the impact of trade policy on the labor market distortion of firms, using China’s accession to WTO in 2001 as a major shift in the country’s trade policy regime. My empirical model compares changes in the measured distortion between firms located within the same local labor market, yet exposed differentially to trade shocks due to their industry affiliations, following the popular approach in the empirical trade literature, as in Pavcnik (2002), Amiti and Konings (2007), Topalova and Khandelwal (2011), and Brandt et al. (2017). I find strong empirical support for my theoretical predictions. Qualitatively, increased import competition due to lower output tariffs leads to an increase in labor market distortion. Even though the effect is consistent with the theory, the magnitude and the statistical significance of this effect are small. On the other hand, access to cheaper inputs due to lower input tariffs causes a significant decrease in labor market distortion. I estimate that China’s lowering of input tariffs during the sample period from 1998-2007 reduced labor market distortion by about 3% on average.

Summarizing the results, my analysis suggests that labor market distortions were substantial and pervasive in China’s manufacturing sector during the sample period. An important finding is that local labor market power accounts for a major part of overall labor market distortion. Trade policy, by changing the aggregate profitability of a sector, can induce entry and exit of firms across local labor markets, and thus, affects distortion in these markets. These findings suggest novel effects of trade policy that deviate from the conventional trade models.

Related Literature

Theoretically, my paper builds on the international trade and labor market imperfections literature. Most related to my modeling approach of the constant elasticity of substitution (CES) labor supply system is the study by Berger, Herkenhoff and Mongey (2019). In their paper, the CES labor supply system is micro-founded from the discrete choice model of each
individual worker, much like how the CES demand system is derived. My contribution is to embed this CES labor supply system into a canonical trade model of Melitz (2003), and allow trade policy to affect the local labor market competition through entry and exit of firms. By modeling the product market as monopolistic competition with constant markups, I can abstract from the complication of strategic interactions in the product market and specify a simple equilibrium selection rule to close the model, following the modeling technique in Atkeson and Burstein (2008), Eaton, Kortum and Sotelo (2012), and Edmond, Midrigan and Xu (2015). There are a few previous studies that also integrate labor market imperfections into trade models with heterogeneous firms. Most recently, MacKenzie (2018) develops and estimates a quantitative trade model with oligopoly in the product market and oligopsony in the labor market, using Indian plant-level data. However, due to the complexity of the strategic interactions in both markets, he has to assume that the number of active firms in the market is exogenous, and trade affects the labor market power through changes in product market power, a mechanism distinct from my model. Jha and Rodriguez-Lopez (2019) specify a trade model with monopolistic competition in the product market and monopsonistic competition in the labor market to reexamine the welfare implications of trade. Helpman, Itskhoki and Redding (2010) and Amiti and Davis (2011) also incorporate labor market imperfections into trade models. However, a common feature of these studies is that, because labor market distortion is captured by fixed parameters, there is little room for trade to endogenously affect the distortion.

Methodologically, my paper is related to the productivity, markup, and pass-through estimation literatures. Recently, productivity estimation has been used to measure and study market power in product market, for example, as in De Loecker and Warzynski (2012), Flynn, Gandhi and Traina (2019). In trade literature, the impact of trade policy on market power in product market has attracted a large attention, including De Loecker (2011),

\footnote{In a related framework, Card et al. (2018) also develops a microfoundation for the monopsonistic competition structure of the labor market based the discrete choice framework. However, the monopsonistic competition is not well-suited for my study because by setup, the labor market distortion is assumed to be constant and cannot be affected by trade.}
De Loecker et al. (2016), Brandt et al. (2017). A growing literature has also adopted the productivity framework to study market power of firms in factor markets, including Morlacco (2018), Brooks et al. (2019), Dobbelare and Wiersma (2019). A common estimation framework used in these studies is the method developed by a series of papers, including Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015) (henceforth, ACF). A drawback to the ACF approach is that identification of the production function requires a Leontief functional-form assumption, which in the Chinese firm-level context significantly overestimates the labor elasticity and produces unrealistically large measures of the labor market distortion.\(^8\)

In this paper, I adopt the Gandhi, Navarro and Rivers (2017)’s method (henceforth, GNR) to consistently estimate labor market distortion at the firm level. My estimation procedure does not impose functional-form assumptions and produces more reasonable estimates.\(^9\) To complement the production function approach, I also adopt insights from the pass-through estimation literature, as in Amiti, Itskhoki and Konings (2018), to measure the endogenous component of the distortion. In this literature, the pass-through of international shocks to firm-level domestic prices is allowed to be dependent on firm’s market share within an industry. The local labor market share plays a similar role in my analysis and permits a variable pass-through rate from a productivity shock to wage paid by a firm.

Finally, my analysis of the labor market distortion in this paper is broadly related to a large literature on resource misallocation due to market imperfections, including Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Edmond, Midrigan and Xu (2015), Morlacco (2018) and Liu (2019), among others. In my analysis, labor market distortion is a form of “labor tax” that potentially impedes a more efficient reallocation of labor in response to trade shocks. My empirical results suggest that labor market distortion is large and on par

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\(^8\)I estimate labor market distortion using the ACF approach and show these results in Table A2 in the Appendix.

\(^9\)Recently, Lu, Sugita and Zhu (2019) also adopt the GNR approach to jointly estimate a constant markup and variable wage markdowns, and study the impact of foreign investment on wage markdowns in China.
with product market distortion, yet only the latter of which has been incorporated into the welfare calculations of trade, as in Arkolakis, Costinot and Rodriguez-Clare (2012), Arkolakis et al. (2018), and others.

1.2 Labor Market Distortion and Theoretical Motivations

This section formalizes the notion of labor market distortion and develops a tractable model to study the impact of a trade policy reform on firms’ competitive conduct in the labor market. To achieve these goals, in section 1.2.1, I derive a “reduced-form” representation of the labor market distortion from firms’ profit maximization problem, and conceptually distinguish between the exogenous versus the endogenous components of the distortion. This “reduced-form” representation is important, because it provides me with a nonparametric framework to measure the overall distortion from production data, without having to impose any structure on either the product or the labor market. In section 1.2.2, I develop a richer model to capture the main sources that give rise to the endogenous distortion of firms. The model also serves to clarify the mechanism through which firms endogenously respond to changes in the competitive environment due to trade shocks.

1.2.1 Labor Market Distortion

Labor market distortion reflects inefficiencies in the labor market. These inefficiencies can arise from policy interventions and institutional constraints, or via externalities and non-competitive conducts of firms in the labor market. Regardless of the source and the interpretation, labor market distortion can be viewed as a form of “labor tax” and has two important properties. First, it raises the marginal wage cost: for every dollar spent on an additional worker, firms have to pay an extra amount to cover the distortion payment. Second, this extra payment reflects the size of inefficiency that inflicts a dead weight loss on the
economy due to firms’ suboptimal level of production.

To be as general as possible about its formulation, I introduce labor market distortion into firm $i$’s profit maximization problem by classifying the distortion into two major components: (1) an exogenous policy distortion and (2) an endogenous labor market power distortion (henceforth, the *exogenous distortion* and the *endogenous distortion* respectively).\(^{10}\) The policy distortion is captured by a distortionary wedge $\chi^{x}$ and manifests as a uniform “labor tax” imposed on the labor supply curve facing all firms within the same labor market. This approach follows the modeling convention in the misallocation literature, for example as in Hsieh and Klenow (2009), Liu (2019). On the other hand, the labor market power distortion arises due to an upward-sloping labor supply curve facing each individual firm $w(L_i)$. A classic example of this distortion is when the firm faces a monopsonistic labor market (Manning (2003)). In such an environment, the wage offer becomes a nontrivial primitive function of labor supply and thus, gives the firm some degree of freedom to set the wage. In what follows, I define the firm’s problem, and derive a “reduced-form” representation to summarize all the distortions in the labor market for each firm.

**Firm’s Problem**

Firm $i$ maximizes its profit by solving the following problem:

$$\max_{L_i} \Pi(L_i) = R(L_i) − (1 + \chi^{x})w(L_i)L_i,$$

where $R(L_i)$ is the revenue of firm $i$, as a function of labor factor $L_i$. $w(L_i)$ is an arbitrary labor supply function facing firm $i$. $\chi^{x}$ represents the policy distortion common to all firms. Notice that this setup is general, in the sense that it does not assume that the labor market is imperfect, nor that workers are homogenous across firms. Such generality is preserved in this

\(^{10}\)The terms “exogenous” and “endogenous” here are used to describe the fact that the former type of distortion generally does not vary across firms and does not respond to firm-level idiosyncratic shocks. On the other hand, the latter type of distortion is dependent on firms’ optimizing decision, and thus generally responds to firm-level shocks.
simple framework because the labor supply function \(w(L_i)\) is allowed to be a constant, i.e. \(w(L_i) \equiv w \forall L_i\), which corresponds to the case of perfect competition. On the other hand, firms with heterogeneous workforce end up solving the same problem as in (1) if workers’ average ability acts as a Hicks-neutral productivity shock for each firm, as in Helpman, Itskhoki and Redding (2010). For the most part of this paper, however, I abstract from this issue, motivated by the fact that the majority of China’s manufacturing employment are low-skilled.\(^{11}\)

First-order condition (FOC) of the problem in (1) yields the following expression:

\[
MRPL_i = (1 + \chi^x)(1 + \frac{\partial w_i}{\partial L_i} L)w_i \tag{1.2}
\]

\[
= (1 + \chi^x)(1 + \chi^e_i)w_i,
\]

where \(MRPL_i \equiv \frac{\partial R_i}{\partial L_i}\) and \(w_i\) are respectively the marginal revenue product of labor and the wage paid by firm \(i\) in equilibrium. Let us further denote \(\chi^e_i \equiv \frac{\partial w_i}{\partial L_i} L w_i\) as the inverse elasticity of labor supply curve. From the expression in (2), it is clear that distortions generate a wedge between the equilibrium marginal revenue product of labor (\(MRPL_i\)) and wage (\(w_i\)) paid by the firm. In a distortion-free economy where there is no policy distortion and the labor market is perfectly competitive, i.e. \(\chi^x = 0\) and \(\frac{\partial w_i}{\partial L_i} = 0\), \(MRPL_i\) is set to equalize the wage \(w_i\) as the firm seeks to maximize profit. The roles of the exogenous distortion \(\chi^x\) and the endogenous distortion \(\chi^e_i\) in firm’s problem are illustrated in the panels A and B of Figure 1.1.

Let us further denote \(\tilde{\chi}_i \equiv (1 + \chi^x)(1 + \chi^e_i)\). From (2), \(\tilde{\chi}_i\) summarizes all the distortions in the labor market, which I henceforth refer to as the overall distortion, and has a “reduced-form” representation as:

\[
\tilde{\chi}_i = \frac{MRPL_i}{w_i} \tag{1.3}
\]

\(^{11}\)In 2004, 88.4% of Chinese manufacturing workers do not have a college degree, of which 53% have only secondary degree, and 35.4% finish high school.
The expression in equation (1.3) is crucial for this study for two reasons. First, the magnitude of $\tilde{\chi}_i$ directly indicates the pass-through rate of an idiosyncratic labor demand shock to the firm’s wage, and hence, carries information about the response of the wage distribution across firms to external shocks. Second, equation (1.3) provides a straight-forward algorithm to estimate the overall distortion based on production data: given the data on wage, the estimation problem of $\tilde{\chi}_i$ translates naturally to the estimation problem of $MRPL_i$, which I accomplish by identifying a revenue production function. This procedure is nonparametric, in the sense that I do not have to impose any assumptions on the product market, the labor market or production technology.\footnote{In the labor economics literature, $\tilde{\chi}_i$ is usually referred to as either the degree of exploitation of workers by firms (Pigou (1924), Robinson (1969), Boal and Ransom (1997)) or the inverse of the wage markdown.}

It is important to point out that in the environment set up by firm’s problem in (1) combined with the FOC expression in (2), the only source of endogenous wage variation in this framework comes from the non-horizontal labor supply curve. In addition, because the elasticity of labor supply depends on the exact position of the firm on the labor supply curve, i.e. the exact value of $w_i$ or $L_i$, the magnitude of this distortion responds endogenously to firm-level demand shocks. Although being useful in guiding measurement and clarifying the basic properties of distortions, the setup in this section is agnostic about what particular sources give rise to the endogenous labor market power distortion of firms and thus, provides little guidance on how international trade might affect such firm-level distortion.

### 1.2.2 A Model of Trade and Endogenous Labor Market Distortion

This section develops a partial equilibrium model of heterogeneous firms with oligopsonistic labor markets and international trade. The goal is to build intuition for the source that gives rise to the firm-level endogenous distortion, and for my subsequent empirical analysis of the impact of a trade policy reform. A tradable goods sector is populated by a continuum of Home (H) firms and Foreign (F) firms, indexed by their productivity $z$, producing differenti-
ated goods.\textsuperscript{13} All Home firms are allocated to a continuum of symmetric local labor markets indexed by \( n \). A unique feature of this model is that firms are small within the sector, but are large within a local labor market. When embedding trade into the model, I assume that the Home firms only sell in their domestic market and compete with the Foreign exports in this market. I also focus solely on a one-sided trade policy liberalization of the Home country to obtain sharp predictions on how Home firms respond to trade policy shocks in the labor market.

**Utility Function**

Product market demand and labor market supply are derived from the utility function of a representative household of the economy. This utility function is specified as follow:

\[
U = C - L, \quad (1.4)
\]

where \( C \) is the sectoral consumption index that increases utility of the household, while \( L \) is the sectoral labor supply index that generates disutility to the household. The consumption index \( C \) is a CES aggregator of the firm-level consumption \( c(z) \) within the sector, similar to Melitz (2003), Atkeson and Burstein (2008), and Edmond, Midrigan and Xu (2015):

\[
C = \left[ \int_{\Omega^H} c^H(z) \frac{\gamma - 1}{\gamma} dz + \int_{\Omega^F} c^F(z) \frac{\gamma - 1}{\gamma} dz \right]^\frac{1}{\gamma - 1}. \quad (1.5)
\]

In equation (1.5), \( \gamma > 1 \) is the constant elasticity of substitution in demand for products across firm \( z \). \( \Omega^H \) and \( \Omega^F \) are respectively the mass of active Home firms and Foreign firms in the Home market.

The labor supply index \( L \) is a multi-location nested CES aggregator, a modeling technique I adopt from the recent labor economics literature (Berger, Herkenhoff and Mongey (2019)).

\textsuperscript{13}In this section, since the productivity index \( z \) uniquely identifies each individual firm, I replace the subscript \( i \) of firm from the previous section by the productivity index \( z \).
More specifically, the representative household allocates labor supply to each location \( n \) such that:

\[
L = \left[ \int_{N^H} L_n^{\frac{\theta + 1}{\eta}} dn \right]^{\frac{\theta}{\eta + 1}} . \tag{1.6}
\]

In equation (1.6), \( \theta > 0 \) is the constant elasticity of substitution of labor supply across labor markets indexed by \( n \). \( N^H \) is the mass of local labor markets within the Home country. Furthermore, within each location \( n \), labor supply is allocated across a finite number of firms \( K_n \) so that \( L_n \) can be decomposed as:

\[
L_n = \left[ \sum_{z \in Z_n} L(z)^{\frac{\eta + 1}{\eta}} \right]^{\frac{\eta}{\eta + 1}} , \tag{1.7}
\]

where \( \eta > 0 \) is the labor supply elasticity of substitution across firms \( z \) within a local labor market \( n \). \( Z_n \) is the productivity set of all active firms in the local labor market \( n \), with the cardinality \( |Z_n| = K_n \).\(^{14}\) I assume that \( \eta > \theta \), which implies that firms are closer alternatives within a location, as compared to firms across locations, in the representative household’s perspective. Berger, Herkenhoff and Mongey (2019) provide a micro-foundation for the aggregate labor supply system specified in equations (1.6) and (1.7), based on a discrete choice model where each individual worker makes labor supply decision to each firm to maximize his(her) utility.\(^{15}\) Their argument is similar to one employed in the product market to justify the aggregate CES demand system, and is recently used elsewhere in the labor economics literature as in Card et al. (2018). The structures in (4), (5), (6), and (7) are now sufficient to derive the product demand and labor supply facing each firm.

\(^{14}\)From this setup, the mass of Home firms would be \( \Omega^H = \int_{N^H} K_n dn \). For symmetric local labor markets, \( K_n = K \), \( Z_n = Z \) for all \( n \), and hence \( \Omega^H = K N^H \).

\(^{15}\)The labor supply system in this paper and in Berger, Herkenhoff and Mongey (2019) could be micro-founded from either a static or dynamic discrete choice framework for each individual worker. As shown in Berger, Herkenhoff and Mongey (2019), each worker has random preferences for working at a particular firm, and the elasticity parameters \( \eta \) and \( \theta \) govern the distribution of this random preferences, conditional on the wage offers by the firms. This micro-foundation approach is used widely for the product demand system that also gives rise to the nested-CES demand in equation (1.5) (see also Anderson, De Palma and Thisse (1987), Verboven (1996)).
Product Demand

From the aggregate demand system in equation (1.5), the demand function facing each firm $z$ is:

$$c(z) = p(z)^{-\gamma} P^{\gamma-1} I,$$

(1.8)

where $P$ and $I$ are respectively the exogenous aggregate price index and aggregate income spent on the sector. Firm $z$ takes the aggregate price index $P$ as given in its optimization problem because it is small within the sector, whereas the aggregate expenditure $I$ depends on the broader structure of the economy and is assumed to be predetermined. The aggregate price index can be shown to have the following form:

$$P = \left[ \int_{\Omega^H} p^H(z)^{1-\gamma} dz + \int_{\Omega^F} p^F(z)^{1-\gamma} dz \right]^{\frac{1}{1-\gamma}}. \quad (1.9)$$

Production Technology

The Home firms only produce and sell in the domestic market. Firm has productivity level $z$, incurs a fixed cost $f$ in terms of a numeraire good, and uses labor as the only factor of production to produce output $y(z)$:

$$y(z) = c^H(z) = zL(z), \quad (1.10)$$

where $L(z)$ is the labor factor use in production of firm $z$. The presence of the fixed cost $f$ allows for an endogenous form of entry and exit, which will be the main mechanism through which trade policy reform affects the labor market equilibrium in this model.
Labor Supply

From the aggregate labor supply system in equations (1.6) and (1.7), the labor supply function facing each firm $z$, located in labor market $n$, can be derived as:

$$L(z) = w(z)^n W_n^{\theta - \eta} \Lambda. \quad (1.11)$$

In equation (1.11), $\Lambda$ is an aggregate labor supply shifter of the sector at the national level in the Home country. Recall that in this model, local labor markets are symmetric, thus $W \equiv W_n \forall n$ is a local labor market wage index, specified as:

$$W = \left[ \sum_{z \in Z} w(z)^{1+\eta} \right]^{\frac{1}{1+\eta}}. \quad (1.12)$$

Since local labor markets are small as compared to the national economy, $\Lambda$ is exogenously given to each firm. However, in contrast to the product market, because firms are large within a local labor market, the local labor market wage index $W$ is endogenous from firm $z$’s perspective. Due to this particular feature of the model, firms exhibit a strategic distortion in the local labor market. In other words, firm $z$’s wage offer $w(z)$ (or employment level $L(z)$) affects the aggregate local labor market wage (employment) index.

Firm-level Equilibrium and Endogenous Distortion

A Home firm $z$ chooses its price $p(z)$ and wage $w(z)$ to solve for the following profit maximization problem:

$$\Pi(z) = p(z)c(z) - w(z)L(z) - f, \quad (1.13)$$

where each endogenous variable $p(z), c(z), w(z), L(z)$ is subject to the constraints given by equations (1.8)-(1.12). To focus on the endogenous distortion, notice that I have set $\chi^x = 0$ in the firm’s problem in equation (1.13), as compared to the problem in equation (1.1).
such that the firm only has to decide the optimal employment level $L(z)$, similar to problem in (1.1). Taking the FOC, I obtain the following expression for the endogenous labor market distortion of firm $z$:\textsuperscript{18}

$$
\tilde{\chi}^e(z) = 1 + \chi^e(z) = \frac{MRPL(z)}{w(z)} = (1 - s_z)\left(1 + \frac{1}{\eta}\right) + s_z\left(1 + \frac{1}{\theta}\right).
$$

(1.14)

In equation (1.14), $s_z$ is the wage-bill share of firm $z$ within the local labor market:

$$
s_z = \frac{w(z)L(z)}{\sum_{z' \in Z} w(z')L(z')}.
$$

(1.15)

Equations (1.14)-(1.15) provide key intuition for the sources of the endogenous distortion $\tilde{\chi}^e(z)$. In particular, $\tilde{\chi}^e(z)$ depends on two key parameters: within-market ($\eta$) and across-market ($\theta$) elasticity of substitution of labor supply, and firm’s own local labor market share $s_z$. When the firm accounts for an infinitesimal share of the local labor market such that $s_z \to 0$, the endogenous distortion reach the lower-bound of $(1 + \frac{1}{\eta})$. On the other hand, a monopsonist employer with $s_z = 1$ incurs a distortion with the magnitude of $(1 + \frac{1}{\theta})$, the upper-bound of the distortion in this model.\textsuperscript{19}

**Entry Game and Market Equilibirum**

I allow for the endogenous entry and exit of firms within the local labor market in response to aggregate sectoral trade shocks. This is motivated by the observed empirical patterns that trade shocks induce endogenous entries and exits, and in turns, affect employer concentration within local labor markets. The entry game follows closely the modeling approach for oligopoly models in international trade, such as those in Atkeson and Burstein (2008), Eaton, Kortum and Sotelo (2012), Edmond, Midrigan and Xu (2015). The only difference in

\textsuperscript{18}The derivation of equation (1.14) is provided in the theory appendix.

\textsuperscript{19}Recall that $\eta$ is assumed to be greater or equal to $\theta$. Therefore, $\frac{1}{\theta} \geq \frac{1}{\eta}$. When all firms are infinitesimally small within the local labor market, the distortion converges to the constant $\frac{1}{\eta}$, which is equivalent to the case of monopsonistic competition in the labor market (see also Jha and Rodriguez-Lopez (2019)).
this model is that firms compete strategically in the labor market rather than in the product
market.

To start with, I assume that the Home firms within a local labor market play a static
Cournot game of quantity competition, i.e., firms choose the optimal employment level so as
to maximize their profit, incorporating the effect of its own action and the action of other
local firms on the local labor market. Each symmetric local labor market $n$ has access to an
integer number of potential firms, with productivity being ranked as:

$$z^{(1)} > z^{(2)} > z^{(3)} > ... > z^{(k)} > ...$$  \hspace{1cm} (1.16)

I focus on the equilibrium where firms make sequential entry decisions based on the decreas-
ing order of their productivity ranking. In particular, the most productive firm $z^{(1)}$ makes
the entry decision first, followed by the second-most productive firm $z^{(2)}$, and so on. When
making entry decisions, each firm can compute perfectly what its profit would be, knowing
that all the more productive players have already entered the market. Firm $z^{(k)}$ decides to
operate in the market as long as its profit is greater or equal to zero:

$$\Pi^K(z^{(k)}) \geq 0.$$  \hspace{1cm} (1.17)

Notice that in equation (1.17), the profit function now has a superscript $K$. The sole purpose
of this superscript is to explicitly indicate that the number of active firms in the local
labor market enters the profit calculation of the firm $z^{(k)}$. Proposition 1 below defines the
equilibrium of the model, its existence as well as its uniqueness.

**Proposition 1** An equilibrium in the environment set up by equations (1.5)-(1.12), in which
firms make sequential entry decisions based on the decreasing order of their productivity
ranking, is fully determined by the equilibrium number of active firms $K^*$ in each local labor
market. A unique equilibrium $K^*$ exists such that no firm has incentives to enter or exit the
market. In the equilibrium with $K^*$ firms, the least productive firm operating in the market
is \( z^{(K^*)} \).

**Proof. See the Appendix.**

Proposition 1 states that the number of firms \( K^* \) sufficiently characterizes a market equilibrium, and that a unique equilibrium with \( K^* \) firms within each local labor market exists. This unique equilibrium arises from the fact that firms are required to make sequential moves by their productivity ranking, and from a so-called *profit monotonicity* condition, specified as follows:

\[
\Pi^K(z^{(k)}) \geq \Pi^{K+1}(z^{(k)}) \geq \Pi^{K+1}(z^{(k+1)}),
\]

(1.18)

Intuitively, equation (1.18) states that more productive firms always have higher profit than less productive firms given any market conditions (the latter inequality). Not only so, more productive firms earn higher profit if there are fewer active firms, i.e., less competition, in the local labor market (the former inequality). As a result, if one were to observe that the firm \( z^{(k+1)} \) operates in the market, it must be true that the firm \( z^{(k)} \) also operates in that market. The *profit monotonicity* condition (18) allows me to solve for the equilibrium using backward induction, and to show that a unique equilibrium \( K^* \) exists.\(^{20}\)

**Market Equilibrium with Trade Policy**

Trade policy is modeled in this environment using two instruments: the output tariff \( (\tau^O) \), and the input tariff \( (\tau^I) \). The output tariff is the import tariff imposed directly on the Foreign product \( c^F(z) \) sold in the Home market. The input tariff, on the other hand, is the tariff imposed on imported intermediate inputs used by Home firms in the production process. I first focus on the impact of the output tariff on the market equilibrium, and then explore the

\(^{20}\)As in any oligopoly-type models, there are multiple equilibria in this environment. However, these equilibria are often intractable and uninteresting. By requiring firms to make sequential moves in a particular order, I can turn attention to an equilibrium that is most informative. Edmond, Midrigan and Xu (2015) shows in their quantitative exercise that the exact ordering of moves matters little in practice. The term *profit monotonicity* is coined by Eaton, Kortum and Sotelo (2012) when describing the equilibrium in their oligopoly model.
implication of the input tariff when the production function involves an intermediate input, which requires a slight modification of the production function in equation (1.10).

Trade shocks working through changes in the output tariff ($\tau^O$) transmit their competitive pressure to the aggregate price index, i.e. $P(\tau^O)$. This price index in turn shifts the labor demand of firms, and consequently affects the local labor market equilibrium. To see this, in equation (1.9), I assume that the mass of Foreign firms selling in the Home market $\Omega^F$ are subject to an ad-volerum tariff $\tau^O$ such that the price received by the Foreign firms, denoted by $p^{F*}(z)$, is a fraction of the Home market price $p^{F}(z)$:

$$p^{F}(z) = (1 + \tau^O)p^{F*}(z).$$  \hfill (1.19)

To simplify the model, I also assume that the Home market is small enough so that $\Omega^F$ can be held fixed, and $p^{F*}(z)$ does not respond to changes in the Home market environment. It is straightforward to rewrite equation (1.9) in the following form and show that the aggregate price index $P$ is an increasing function of the output tariffs $\tau^O$:

$$P(\tau^O) = \left[ \int_{\Omega^H} p^{H}(z)^{1-\gamma} dz + (1 + \tau^O)^{1-\gamma} \int_{\Omega^F} p^{F*}(z)^{1-\gamma} dz \right]^\frac{1}{1-\gamma},$$  \hfill (1.20)

where $P'(\tau^O) \geq 0$. The labor demand curve in this model, i.e. the $MRPL(z)$ curve, can be derived as:

$$MRPL(z) = z^{\frac{2-1}{\gamma}} L(z)^{-\frac{1}{\gamma}} P(\tau^O)^{\frac{2-1}{\gamma}} \Phi,$$  \hfill (1.21)

where $\Phi > 0$ is an aggregate constant. As can be seen from equations (1.20)-(1.21), tariff changes affect the aggregate price index $P(\tau^O)$ and shift the $MRPL(z)$ curve. Firms observe these changes in the aggregate environment, re-calculate their profit taking into account the competition structure in the labor market, decide if they should operate, and if operating, the optimal level of employment $L^*(z)$.

From proposition 1 and starting from the equilibrium with a high-level output tariff, there
exists a “cut-off” firm which represents the lowest productivity firm operating in the market, i.e. \( z^{(K^*)} \). When the output tariff is lowered, competitive pressure drives down each Home firm’s profit. This makes the operating decision of low productivity firms near the “cut-off” less profitable, for example \( z^{(K^* - 1)} \), \( z^{(K^*)} \), and induces exit of these firms. As a result, the equilibrium number of firms decreases, local labor market shares are reallocated towards surviving firms, and the average distortion increases in the local labor market.\(^{21}\) I summarize the implications of a change in the output tariff on the local labor market equilibrium with proposition 2.

**Proposition 2 (Equilibrium with Output Tariff)** Under the environment set up by equations (1.5)-(1.12), in which firms make sequential entry decisions based on the decreasing order of their productivity ranking, lowering output tariffs \((\tau^O)\) induces exit of less productive firms, reallocates local labor market shares towards more productive firms, and increases the average endogenous distortion in the local labor market. Formally, \( K^*'(\tau^O) \geq 0 \), and for \( \forall z \geq z^{(K^*)} \), \( s'(\tau^O,.) \leq 0 \), \( \tilde{\chi}e'(\tau^O,.) \leq 0 \).

**Proof.** See the Appendix.

To consider the effect of an input tariff change, I need to modify the production function in equation (1.10) to involve an intermediate input. Specifically, the modified production function is as follow:

\[
y(z) = c^H(z) = zL(z)^{\alpha}M(z)^{1-\alpha},
\]

where \( M(z) \) is the intermediate input used by firm \( z \), and \( \alpha \) is the factor share of labor. Firms still need to incur a fixed cost \( f \) in terms of a numeraire good to produce goods. The price of intermediate input is determined by the world market, i.e. perfectly competitive,

\(^{21}\)This mechanism is similar to the canonical Melitz (2003) model. However, in Melitz (2003), there is no labor market distortion. Jha and Rodriguez-Lopez (2019) allow for labor market distortion in Melitz (2003)’s environment, but assume such distortion to be constant, and thus, not responding to competitive trade shocks.
and subject to the Home country’s input tariff ($\tau^I$). More formally:

$$p_M = p_M^{World}(1 + \tau^I).$$  

(1.23)

From the equations (1.22)-(1.23), lowering the input tariff has an intuitive effect on the firm-level labor demand. Specifically, lowering the input tariff induces firms to use more intermediate input, which through the production function, increases the marginal revenue product of each worker. Therefore, in contrast to the impact of lowering the output tariff, lowering the input tariff decreases production costs, drives up profit, and induces entries of firms that ex-ante has productivity below the “cut-off” firm, for example $z^{(K^*+1)}$, $z^{(K^*+2)}$, ...

Furthermore, the magnitude of the effect by the input tariff is magnified by a factor of $\frac{1-\alpha}{\alpha}$, which is the ratio of factor shares between labor and intermediate input. The impact of the input tariff on market equilibrium is summarized by proposition 3.

**Proposition 3 (Equilibrium with Input Tariff)** Under the environment set up by equations (1.5)-(1.12) and with modifications in equations (1.22)-(1.23), in which firms make sequential entry decisions based on the decreasing order of their productivity ranking, lowering input tariffs ($\tau^I$) induces entry of less productive firms, reallocates local labor market shares towards new entrants, and decreases the average endogenous distortion in the local labor market. Formally, $K^*(\tau^I) \leq 0$, and for $\forall z \geq z^{(K^*)}$, $s'(\tau^I,.) \geq 0$, $\tilde{\chi}'(\tau^I,.) \geq 0$. Furthermore, compared to the output tariff, the impact of the input tariff is magnified by $\frac{1-\alpha}{\alpha}$, the relative factor shares between labor and intermediate input.

**Proof. See the Appendix.**

Proposition 3 concludes my theoretical analysis. Before moving on to the empirical analysis, it is important to point out that all the predictions in propositions 1-3 still hold true if the product market is assumed to be perfectly competitive.
1.3 Measuring Labor Market Distortion

This section develops a production-based framework to estimate the overall distortion at the firm-level. As will be clear shortly, identification of the production function, and hence labor market distortion, comes from the plausible assumptions of firm’s decision making, rather than any structural assumptions on either the product or the labor market. Section 1.3.1 sketches out an estimation approach based on a nonparametric method, building on the recent work by Gandhi, Navarro and Rivers (2017) on production function estimation. Section 1.3.2 briefly describes the data on Chinese manufacturing firms used in estimation, and section 1.3.3 presents the main empirical results of measured distortion.

1.3.1 Estimating Distortion from Production Data

My estimation strategy of the labor market distortion follows directly from equation (1.3). To simplify notation, I omit the subscript $i$ when it does not cause any confusion. It is convenient to rewrite the expression of the distortion in equation (1.3) as a ratio between the revenue elasticity of labor and the wage-bill share of total revenue as follows:

$$\tilde{\chi} \equiv \frac{MRPL}{w} = \frac{\partial r}{\partial L} = \frac{\partial r}{\partial l} \equiv \frac{wL}{R},$$

(1.24)

where $r$ and $l$, respectively, are the natural logs of total revenue and labor factor.\footnote{Notice that the wage-bill share of total revenue here ($\alpha^L$) is the expenditure share on labor within each firm, and distinct from the local labor market wage-bill share defined in section 1.2, which aims to measure the labor market share of each firm within a location.} Denoting the revenue elasticity of labor as $\theta^L \equiv \frac{\partial r}{\partial l}$, and the wage-bill share of total revenue as $\alpha^L \equiv \frac{wL}{R}$, the distortion $\tilde{\chi}$ in equation (1.24) could now be expressed in the following short-form:

$$\tilde{\chi} = \frac{\theta^L}{\alpha^L}.$$  

(1.25)
Since information about the wage-bill is readily available in most production datasets, the task now is to estimate the revenue elasticity with respect to labor (θ_L) from a revenue production function. To achieve this goal, I begin by specifying a revenue production function of firm in the log-form as follows:

\[ r_t = f(k_t, l_t, m_t) + \omega_t + \varepsilon_t, \]  

(1.26)

where \( r_t, k_t, l_t, m_t \) are the natural logs of revenue, capital, labor, and material. \( \omega_t \) measures the revenue productivity, i.e. revenue TFP, in period \( t \), and \( \varepsilon_t \) is a random measurement error. Here, \( f(.) \) is a revenue production function, and allowed to be nonparametric.23

**Identification and Estimation of Production Function**

To identify and estimate the revenue production function specified in equation (1.26), I build on a recent nonparametric estimation method proposed by Gandhi, Navarro and Rivers (2017), henceforth, the GNR method. As is common in the productivity literature, identification of the production function in the GNR method is rooted in the timing assumptions in decision making by the firm. However, in constrast to other existing methods such as those proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015), GNR exploits an additional restriction derived from profit-maximizing behavior of the firm with respect to materials to identify the revenue elasticity of this input. In what follows, I provide a brief description of how I adapt the GNR method to identify and consistently estimate the revenue elasticity of labor, \( \theta_L \). A distinct feature of my approach as compared to the original GNR method is that I do not need to assume perfect competition in the product market, since my goal is to identify a revenue production function.

My estimation procedure is implemented in two stages. In the first stage, firm’s profit-maximizing behavior with respect to material is exploited to provide identification infor-

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23 The specification of the (log) revenue production function in equation (1.26) could be microfounded within a large class of demand structures that dictate the firm-specific price as a power function of quantity. See De Loecker (2011) for an example.
mation for the revenue elasticity of material, i.e. $\frac{\partial r(\cdot)}{\partial m}$. 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. In this case, I assume that the market for material is relatively frictionless, and hence, material expenditure share is informative about the revenue elasticity of this factor. Following GNR, in the first-stage, I estimate the following share-regression using a nonlinear least-square (NLS) procedure:

$$\log(s^M_t) = \log \frac{\partial}{\partial m_t} f(k_t, l_t, m_t) - \varepsilon_t. \quad (1.27)$$

In equation (1.27), $s^M_t$ is the expenditure share of material obtained directly from the data, and is defined as $s^M_t = \frac{p^M_t M_t}{R_t}$. The nonparametric elasticity function $\frac{\partial f(\cdot)}{\partial m_t}$ is approximated by a second-order polynomial sieve. The estimation of equation (1.27) provides me with two outputs to use in the second stage: the revenue elasticity of material $\frac{\partial f(\cdot)}{\partial m_t}$, and the random shock $\hat{\varepsilon}_t$.

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

$$\int \frac{\partial}{\partial m_t} f(k_t, l_t, m_t) dm_t = f(k_t, l_t, m_t) + C(k_t, l_t) \equiv D^\varepsilon(k_t, l_t, m_t). \quad (1.28)$$

Plug the expression in equation (1.28) back to the original specification of production function in equation (1.26), I can rewrite the productivity term as:

$$\omega_t = (r_t - \varepsilon_t - D^\varepsilon(\cdot)) + C(k_t, l_t). \quad (1.29)$$

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24In principle, material could be subject to market frictions as well. To alleviate the concerns about frictions in this market, I control for an extensive set of exogenous state variables that could affect the material demand decisions. Therefore, as long as firms do not possess market power in the market for material, estimating its 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).

25The derivation of this share-regression from firm’s FOC is provided in the Appendix.
Following the productivity literature, firm productivity is assumed to follow a flexible Markov process:

\[ \omega_t = h(\omega_{t-1}) + \eta_t, \]  

(1.30)

where \( \eta_t \) is an exogenous productivity shock to the firm at time \( t \). Importantly, the exogeneity assumption imposed here is that \( k_t \) and \( l_t \) are predetermined, and do not respond to \( \eta_t \). In other words, I assume that capital and labor factors are subject to planning, and chosen based solely on the information about the expected productivity captured by \( h(\omega_{t-1}) \). The only factor that responds to the productivity shock \( \eta_t \) is the material \( m_t \), the elasticity with respect to which is already identified in the first stage. The Markov productivity process in equation (1.30) provides exclusion restrictions needed to identify the function \( C(\cdot) \). Let’s denote \( \Psi_t \equiv r_t - \varepsilon_t - D^\varepsilon(\cdot) \), and combine equations (1.29)-(1.30), I can now rewrite the Markov productivity process as:

\[ \Psi_t = -C(k_t, l_t) + h(\Psi_{t-1} + C(k_{t-1}, l_{t-1})) + \eta_t. \]  

(1.31)

Equation (1.31) nonparametrically identifies \( C(\cdot) \) and \( h(\cdot) \), and in turn, provides identification of the revenue production function. Estimation of equation (1.31) is performed using a GMM procedure.\(^{26}\) In my estimation, other than primary factors such as capital and labor, I also control for a vector of state variables that may affect input demand decision of firms, including year, location and industry fixed effects, firm’s ownership type, export status, and tariff levels associated with the firm’s industry.

**Compute the Distortion**

Given estimates from the revenue production function, I can now compute the empirical measure of the labor market distortion expressed in equation (1.25). Since \( \varepsilon_t \) is a random measurement error, and does not affect firm’s labor demand decision, I need to correct for

\(^{26}\)See details of this GMM procedure in section 1.B of the Appendix.
this term in calculating the *expected* revenue that enters the denominator of the distortion in equations (1.24)-(1.25). The estimation of equation (1.27) in the first stage does provide me with an estimate of the measurement error, i.e. $\bar{\varepsilon}_t$. The measure of the distortion, therefore, can be computed as:

$$\bar{\chi} = \frac{\hat{\theta}^L}{\hat{\alpha}^L} = \frac{\partial \hat{\varepsilon}(.)}{\partial l} \times \exp(\hat{\varepsilon}_t).$$

(1.32)

This final step concludes my estimation procedure for the *overall* labor market distortion, which is based solely on the production function estimation approach.

### 1.3.2 Chinese Firm-level Data

The Chinese firm-level data comes from China’s Annual Survey of Industrial Enterprises (ASIE) from 1998 to 2007. This is a rather standard panel dataset covering all industrial private firms with sales above 5 million Renminbi (RMB) and all state-owned enterprises (SOEs). The dataset encompasses more than 90% of industrial activities in China in terms of gross output during the sample period (Brandt, Biesebroeck and Zhang (2014)). Table A1 in the Appendix reports the main aggregate statistics of this dataset, which matches with published official statistics from the China’s National Bureau of Statistics, and confirms the dataset’s quality. The dataset contains all variables required for the production function estimation, including total gross output (revenue), capital stock, employment, material (in monetary values). In addition, the dataset also contains information about wage-bill, ownership status, export, detailed geographical code, and firms’ four-digit industry affiliation. My estimating sample consists of about 1.2 million firm-year observations, spanning over 10 years, and 427 four-digit industries. Throughout this paper, the unit for the local labor market in Chinese firm-level dataset is county, which is the lowest-ranked administrative unit that has authority to set labor market regulations such as the minimum wage policy and the *hukou* household registration status. This administrative unit of the local labor market has also been discussed and used in Hau, Huang and Wang (2018), Tombe and Zhu (2019).
final firm-level data cover 460 Chinese counties throughout the sample period.

### 1.3.3 Empirical Measure of Distortion

Table 1.1 reports the empirical results for the revenue elasticites and labor market distortion across 29 two-digit Chinese manufacturing industries. Since my production function is nonparametric, I can recover the distribution of each revenue elasticity and the firm-level distortion within each industry. Across all industries, my estimation procedure’s performance is remarkably stable and produces an average capital elasticity of 0.07, an average labor elasticity of 0.08, and an average material elasticity of 0.75. The average revenue return to scale (RTS), is 0.89. The average magnitude of the labor market distortion $\tilde{\chi}$ estimated for China’s whole manufacturing sector is 1.87, implying an average overall pass-through rate of 53% of an idiosyncratic demand shock to wage. This pass-through rate suggests that, for instance, of a productivity shock that increases marginal revenue product of a worker by one dollar, only 53 cents is shared with the worker in the form of wage payment. The median value of estimated distortion is 1.33, indicating that the distribution of firm-level distortion is highly skewed to the right. Across all industries, both the mean and median of the distortion are consistently greater than one. This empirical fact suggests that Chinese manufacturing firms face pervasive frictions in the labor market during the 1998-2007 period.

### Labor Market Distortion across Industries and Years

Given these estimates of the firm-level labor market distortion, I can now investigate its distribution as well as its correlation patterns across industries and years. Figure 1.2 displays the evolution of labor market distortion distribution over three equidistant years within my sample period: 1999, 2003 and 2007. As shown in the figure, across the three years, the distribution of distortion has shifted to the right, with decreases in both the mean and median.

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27If one is willing to impose constant RTS of physical production to the whole Chinese manufacturing sector, this revenue RTS implies the average markup of about 1.12 (or 12%) for the sector. This approach has been developed by Flynn, Gandhi and Traina (2019) to estimate the markup for the US, with the magnitude of US markup in the similar range to what I obtain for China.
Furthermore, the dispersion of distortion distribution has also reduced substantially.\footnote{The reduction in the dispersion of the distortion typically implies that there might be a lesser degree of labor market misallocation over time. This rationale is applied elsewhere in the misallocation literature, for example as in Hsieh and Klenow (2009), Lu and Yu (2015), Morlacco (2018).}

In Figure 1.3, I show the patterns of correlation between the distortion and several two-digit industry characteristics which might potentially be associated with the degree of labor market distortion, including industry’s export share, state ownership share, high-skill employment ratio, and female employment share.\footnote{The high-skill employment ratio is defined as the ratio between the number of workers that finish high-school and the number of workers that finish only secondary-school. The correlation patterns are also robust to using finishing college degree as an alternative measure of skill level.} The data for industry-level characteristics is extracted from the firm-level data for the year 2004, when more detailed information is reported for each firm.\footnote{The year 2004 is a China’s Census year, therefore, more detailed data is collected for each firm (see also Brandt, Biesebroeck and Zhang (2014)).} The top panels of Figure 1.3 illustrate that more export-oriented industries tend to have lower levels of labor market distortion, while industries with higher shares of state ownership exhibit higher levels of distortion. In the bottom panels, industries that employ more female workers tend to have lower distortion, while the reverse is true for industries with larger high-skill employment ratio.

**Labor Market Distortion across Firms**

To examine the correlation patterns of distortion across firms, I correlate firm-level labor market distortions with measured productivity, employment size, export status, ownership status, local labor market concentration, and local minimum wage. As shown in Table 1.2, more productive firms have higher level of labor market distortion, regardless of the covariates included. Conditioning on productivity, larger firms are associated with less distortion. Columns (3)-(5) show that exporting firms and foreign-invested firms incur less distortion, while state-owned enterprises (SOEs) are more distorted in the labor market.\footnote{This is perhaps surprising, given the fact that workers at SOEs typically have lower marginal revenue products (Hsieh and Song (2015)). However, this is consistent with state firms being subject to more frictions in hiring and firing decisions, and in line with empirical results I obtain in section 1.4, where the labor supply elasticity estimated from an exogenous demand shifter for SOEs is much lower.}

Importantly, local labor market characteristics seem to play an important role in deter-
mining the firm-level labor market distortion. Column (5) shows that more concentrated and lower minimum wage labor markets are associated with higher firm-level distortion. This pattern is consistent with the existence of an endogenous source of labor market distortions that arise from local labor market conditions, which I theoretically motivate in section 1.2, and explore further empirically in section 1.4.32

1.4 Labor Market Power as Endogenous Distortion

As described in section 1.2, labor market distortion can be exogenous or endogenous to firm-level shocks. In the sole presence of the exogenous distortion, the firm-level wage does not respond to an idiosyncratic labor demand shock while employment possibly does. This section provides reduced-form evidence that the firm-level wage does respond proportionately along with employment to an exogenous demand shifter, namely the granting of permanent normal trade relations to China by the United States, which was a major trade policy uncertainty shock (henceforth, US-China TPU shock).

By comparing the responses of wage and employment to an exogenous demand shock, I can quantify the magnitude of the endogenous distortion in the labor market. I will show firstly that a firm’s responses in terms of wage and employment imply an upward sloping labor supply curve, with an average elasticity of 2.07. This indicates that the magnitude of the endogenous distortion accounts for almost 80% of the overall distortion measured by the production function approach in section 1.3. And secondly, the pattern of responses is dependent on the firm’s local labor market wage-bill share, which suggests the existence of a strategic component of firms’ noncompetitive conduct in the labor market that is consistent with the theory proposed in section 1.2.

To credibly identify firms’ wage and employment response to an idiosyncratic demand shock, I use the removal of US trade policy uncertainty towards China, which is associated

32The HHI in column (5) is the Herfindahl-Hirschman Index of employer concentration within a county, which is the geographic unit of local labor market in this paper.
with China’s accession to WTO in 2001, as a quasi-experimental demand shifter. The intuition is that the removal of TPU increases the expected profit of entering the export market or expanding export activities, and therefore raises firm-level labor demand. The measurement of TPU and the behavioral response of firms towards TPU removal is modeled and studied by Handley and Limao (2015), Handley and Limão (2017). In the context of China’s accession to WTO, Pierce and Schott (2016) estimate the impact of the US-China TPU shock on US manufacturing employment, and finds that the entry of new Chinese exporters increases significantly following the TPU shock. Handley and Limão (2017) investigate the impact of the US-China TPU shock on US’s imports from China, US prices and welfare. Most importantly, these studies provide robust evidence that the across-industry variation of the US-China TPU shock is largely exogenous from the perspective of Chinese firms. I follow this literature in measuring the TPU shock, and treat such shock as random. However, different from this literature’s focus, my focus is on the relative responses of wage and employment to infer endogenous distortions in the labor market.33

Formally, the US-China TPU shock at four-digit industry level is measured by the gap between the “Column 2” tariffs and the MFN tariffs faced by the Chinese firms.34 Denoting this gap by $\tau_{TPU}^{JT}$, I estimate the following regression model using the OLS method:

$$\log(w_{i,t+1}) = \beta_1 \tau_{JT}^{TPU} + \beta_2 (\tau_{JT}^{TPU} \times s_{ijlt}) + \beta_3 s_{ijlt} + \gamma_i + \gamma_{lt} + \varepsilon_{it}.$$  

(1.33)

In the regression model (1.33), $w_{i,t+1}$ is the observed (real) wage of firm $i$ in year $(t + 1)$.35

33In Handley and Limao (2015) and Handley and Limão (2017), the labor market is assumed to be perfectly competitive, and hence, there is no room for an empirical investigation of labor market distortions.

34“Column 2” tariffs are the tariffs assigned to nonmarket economies under the Smoot-Hawley Tariff Act of 1930. MFN tariffs are the tariffs offered to all members of WTO by the US.

35I use average wage, computed as the ratio of wage-bill and employment to measure the firm-level wage. Wage-bill data is deflated using detailed industry deflators at the four-digit industry level to account for any industry-specific trends, in the spirit of industry partial equilibrium models as in Melitz (2003). The industry deflators are obtained from Brandt et al. (2017).
τ^{TPU}_{jt} is the US-China TPU shock to industry j at year t, and is computed as:

\[ \tau^{TPU}_{jt} = (\text{Column 2 Tariffs}_j - \text{MFN Tariffs}_j) \times PreWTO_t. \] (1.34)

\( \gamma \) and \( \gamma_{lt} \) are firm and location-by-year fixed effects, respectively. \( s_{ijlt} \) is the local labor market wage-bill share of firm \( i \), in industry \( j \), within the location \( l \), and in the year \( t \). This wage-bill share is an empirical counterpart of the share defined in equation (1.15). Specifically, \( s_{ijlt} \) is computed as:

\[ s_{ijlt} = \frac{w_{ijlt}L_{ijlt}}{\sum_i w_{ijlt}L_{ijlt}}. \] (1.35)

Equation (1.33) is estimated with two outcome variables: the (log) wage and the (log) employment.\(^{36} \) I also estimate two versions of equation (1.33): one without \( \beta_2 \) and \( \beta_3 \), and the other with \( \beta_1 \), \( \beta_2 \), and \( \beta_3 \). The goal of this exercise is twofold. First, by comparing the average responses of wage and employment to the common \( \tau^{TPU}_{jt} \) shock, I can identify the average labor supply elasticity of Chinese manufacturing firms. This gives me an estimate of the average endogenous distortion \( \tilde{\chi}_e \) discussed in section 1.2.1. Second, by allowing for a firm’s response to depend on its local labor market share, I can isolate the strategic component of labor market distortion. This approach is used by Berger, Herkenhoff and Mongey (2019) who study firms’ labor market response to tax policy changes in the US, and more generally, in the trade literature to study the variable pass-through rate of international exchange rate shocks to firm-level prices, as in Amiti, Itskhoki and Konings (2018).

Identification of equation (1.33) is obtained by comparing changes in wage and employment of firms within the same location, yet exposed to differential labor demand shocks

\(^{36}\)The regression equation for the (log) employment is:

\[ \log(L_{i,t+1}) = \beta_1 \tau^{TPU}_{jt} + \beta_2 (\tau^{TPU}_{jt} \times s_{ijlt}) + \beta_3 s_{ijlt} + \gamma_i + \gamma_{lt} + \varepsilon_{it}. \] (1.33A)

One could notice that the equations (1.33) and (1.33A) form a seemingly unrelated regression (SUR) system. Since the covariates are identical between the two equations, the OLS method would be equivalent to the SUR estimation method.
due to their industry affiliations. Any common time-varying local labor market shocks are controlled for by inclusion of location-by-year fixed effects. To allow time for firms to adjust their responses, and to alleviate a potential endogeneity concern of local labor market share, I use firms’ outcomes in period \((t + 1)\) as dependent variables to compute my estimates of labor supply elasticity. The coefficients of interest are \(\beta_1^h\) and \(\beta_2^h\), where \(h \in \{w, L\}\). Standard errors are clustered two-way, at firm-level and industry-by-year level, which is the variation level of the US-China TPU shock in these regressions.

Table 1.3 reports the regression results of equation (1.33).\(^{37}\) Columns (1) and (2) report results for equation (1.33) with the (log) wage as the dependent variable, and columns (3) and (4) report results for the same equation with the (log) employment as the dependent variable. Since the US-China TPU shock \(\tau_{jt}^{TPU}\) is measured in log-form, the coefficients can be interpreted as percentage point changes. Let us first interpret the results from columns (1) and (3). Without the share-related covariates, results from these columns show that wage and employment both increased in response to the US-China TPU shock. Specifically, a one percentage point decrease in the “tariff uncertainty gap” \(\tau_{jt}^{TPU}\) leads to a 0.066 point increase in wage and a 0.137 point increase in employment. On average, the change in \(\tau_{jt}^{TPU}\) associated with China’s accession to WTO is about 25 percentage points at the four-digit industry level, implying that the manufacturing wage and employment increased 1.65% and 3.43% respectively, due to the reduction in US-China TPU. More importantly, for the purpose of this study, these results suggest that the response of wage, i.e. \(\frac{d\log(w)}{d\log(\tau_{jt}^{TPU})}\), is about half the size of the response of the employment, i.e. \(\frac{d\log(L)}{d\log(\tau_{jt}^{TPU})}\). This result in turn indicates the average labor supply elasticity faced by a firm is 2.07. Computing the endogenous distortion from this labor supply elasticity implies the magnitude of endogenous distortion of 1.48. Compared with my average estimates from the production function approach in section 1.3, this endogenous distortion accounts for 79% of the overall distortion. This is a key finding.

\(^{37}\)Due to a large number of fixed effects, many singleton groups are automatically dropped out of the sample in my estimation procedure (using Stata’s -reghdfe- routine). Therefore, the number of observations is smaller than those used for the production function estimation reported in Table 1.1. See also Correia (2016) for more details on this estimation procedure.
of the paper.

Estimation results in columns (2) and (4) further show that firms’ response is nonlinear and varies by firms’ local labor market share. This is reflected through the sign and magnitude of $\beta^h_2$. The interaction terms are positive and significant in both columns, suggesting that the response of firms with larger local labor market share is weaker to the US-China TPU demand shock.\footnote{This result resonates with the findings by Berger, Herkenhoff and Mongey (2019), in which the authors exploit changes in corporate taxes, rather than international trade shocks, to identify the endogenous distortion for the US.} To be more specific about the implication of these interaction coefficients, let us calculate the share-dependent labor supply elasticity based on the following formula:

$$\eta(s_{ijlt}) = \frac{d\log (L_{i,t+1})}{d\log (w_{i,t+1})} = \frac{\frac{d\log (L_{i,t+1})}{d\pi^T_{jlt}}}{\frac{d\log (w_{i,t+1})}{d\pi^T_{jlt}}} = \frac{\beta^L_1 + \beta^L_2 s_{ijlt}}{\beta^w_1 + \beta^w_2 s_{ijlt}}. \quad (1.36)$$

Given the formula in equation (1.36), it is useful to look at the labor supply elasticity for some particular values of $s_{ijlt}$. In Chinese firm-level data, the average local labor market share has decreased from about 0.3 in 1998 to 0.18 in 2007. Plugging these numbers into equation (1.36), an average share of 0.3 implies the value of $\eta(0.3)$ is 2.05. An average share of 0.18 implies the value of $\eta(0.18)$ is 2.21. Firms with very small labor market share, i.e. $s \to 0$, would face an elasticity of about 2.34, while firms that account for a very large share of the local labor market, 0.8 for instance, would face a labor supply elasticity of about 0.6.

As a consequence, the endogenous distortion implied by the estimates in column (2) and (4) is much larger for firms that are the primary employers within a local labor market, i.e. these firms face a highly inelastic portion of the labor supply curve. To further illustrate the variation of labor supply elasticity as a function of local labor market share, Figure 1.4 graphs the computed elasticity based on equation (1.36). The range of elasticity is from 0.6 to 2.5, with 95% of firms facing an elasticity ranging from 1.16 to 2.36.\footnote{The estimated coefficients restrict the ability to infer the elasticity for firms with labor market share $s_{ijlt} \geq 0.882$. This implies that there might be further nonlinearity in the response of firms to the TPU shock, which I do not explore in this paper. However, there are less than 10\% of firm-year observations that dominate the whole market, and I exclude these firms in my subsequent analyses when it involves the endogenous distortion measured by the reduced-form approach.}
The results in Table 1.3 provide clear evidence that an endogenous form of labor market distortion exists. Such endogenous distortion accounts for almost 80% of the overall distortion measured by the production function approach in section 1.3. Furthermore, the distortion is significantly dependent on the local labor market share of firm. It is therefore possible to come up with a measure of the endogenous distortion that varies by firms’ local labor market share.

A Measure of Share-Dependent Endogenous Distortion

I use the share-dependent labor supply elasticity calculated by equation (1.36) to compute a measure of share-dependent endogenous distortion, the variation of which arises due to the actual variation of the local labor market share in the data. More specifically, from the share-dependent labor supply elasticity in equation (1.36), this measure of the endogenous distortion can be computed as:

\[
\tilde{\chi}^e(s_{ijlt}) = 1 + \frac{1}{\eta(s_{ijlt})}.
\]  

(1.37)

Measure of \(\tilde{\chi}^e(s_{ijlt})\) as in equation (1.37) is consistent with the theory in section 1.2. However, it has a disadvantage: the only source of its variation comes from \(s_{ijlt}\). In other words, measuring the endogenous distortion from the reduced-form approach as in equation (1.37) assumes that the structural parameters of the labor supply system in equations (1.6)-(1.7) are constant across industries and years. However, this measure is still useful and can serve two purposes: (1) it can help to cross-validate the measure of the distortion from the production function approach in section 1.3, and (2) it can illustrate how the response of local labor market shares to trade shocks translates directly to changes in labor market distortion.

To cross-validate the reduced-form measure with the production function measure, Figure 1.5-1.6 reproduce Figure 1.2-1.3, respectively. The evolution and correlation patterns are remarkably similar between the two measures. Specifically, in the right panel of Figure
1.5, the distribution of this endogenous distortion is becoming less dispersed over time and associated with reductions in both the mean and median. In terms of industry characteristics in Figure 1.6, industries that are more export-oriented and employ more female workers are also associated with lower level of labor market distortion. On the other hand, industries that have higher shares of state ownership and high-skill workers are associated with greater distortions. The only differences between the two measures are the absolute level of distortion and its across-firm dispersion, which is illustrated in the right panel of Figure 1.5. Since its only source of variation comes from the local labor market share, the distribution of the reduced-form measure is much less dispersed as compared to the production function measure. In section 1.5, I compare the response of both measures to a trade policy reform, and show that they exhibit broadly similar patterns.

1.5 Impact of China’s Trade Policy Reform

A key interest in this paper is to understand how China’s own trade policy reform affected labor market distortion. In section 1.5.1, I briefly describe changes in China’s trade policy regime associated with its accession to WTO in 2001. In section 1.5.2, I specify empirical models used to establish a causal relationship between China’s trade policy reform and firm-level labor market distortions.

1.5.1 China’s Trade Policy Regime upon WTO Accession

China’s accession to WTO in December 2001 represents a major shift in China’s trade policy regime over the past three decades. Upon accession, China committed to reduce the import tariffs from an average of 16 percent in the pre-WTO period to an average of 9 percent in the post-WTO period.\(^4\) This paper focuses on the impact of lowering the tariff barriers.

\(^{4}\)Along with the reduction in import tariffs, China also made commiments to substantially reduce other non-tariff barriers upon WTO accession. See Brandt and Rawski (2008) and Brandt et al. (2017) for more institutional context of this event.
Specifically, I consider two policy instruments: the output tariff ($\tau^O$) and the input tariff ($\tau^I$), the empirical counterparts of the theoretical policy instruments in section 1.2. Input tariffs here are defined as input-share weighted averages of the output tariffs, using input expenditure shares from China’s 2002 Input-Output table as weights, following Amiti and Konings (2007)’s approach in measuring input tariffs. In particular, the input tariff for industry $j$ is calculated as:

$$\tau^I_j = \sum_m a_{mj} \tau^O_m,$$

(1.38)

where $a_{mj}$ is the share of expenditure that industry $j$ purchases from industry $m$, and $\tau^O_m$ is the output tariff that China imposes on industry $m$.

In Table 1.4, I provide a summary of China’s tariff evolution over the sample period, from 1998-2007. The cutoff event is at the end of 2001, when China’s official status in WTO became effective. As reported in Table 1.4, along with a reduction in the level of output tariffs, the standard deviation also fell from 9% in 1998 to 6% in 2007, implying that tariffs converged to a more uniform level across industries. A reduction in the standard deviation of tariffs across industries is evidence of the exogeneity of tariff changes, and is commonly deployed in the empirical trade literature examining the effect of tariff liberalization on domestic outcomes (see for example, Amiti and Konings (2007), Topalova and Khandelwal (2011), Loecker et al. (2016), Brandt et al. (2017)). Intuitively, a decrease in the dispersion of tariffs suggests that there is less room for the Home country’s government to cherry-pick protection levels of specific industries due to political economy motives. For input tariffs, the tariff levels decreased from an average of 11% in 1998 to 6% in 2007, and the standard deviation decreased from 3% to 2% in respective years.\footnote{Due to the aggregation level of China’s 2002 Input-Output table, input tariffs only vary at the three-digit industry level, which contributes to the lesser degree of variation in the input tariffs across industries in Table 1.4.}
1.5.2 Empirical Strategy

To investigate the causal impact of tariff liberalization on the endogenous response of firm-level distortion, I adopt a version of the empirical specifications widely used in the empirical trade literature, for examples, as in Pavcnik (2002), Amiti and Konings (2007), Topalova and Khandelwal (2011), and Brandt et al. (2017). The specification is as follows:

\[
\log(\tilde{\chi}_{ijlt}) = \gamma_O \times \tau^O_{j,t-1} + \gamma_I \times \tau^I_{j,t-1} + \gamma_i + \gamma_{cic2,t} + \gamma_{lt} + \varepsilon_{ijlt}. \tag{1.39}
\]

In equation (1.39), the dependent variable is the (log) measured labor market distortion. \(\tau^O_{j,t-1}\) and \(\tau^I_{j,t-1}\) are the one-year lagged output and input tariffs for industry \(j\), computed at four-digit and three-digit aggregation level respectively. \(\gamma_i\) controls for firms’ fixed effects, and \(\gamma_{lt}\) controls for location-by-year fixed effects, similar to the regression in equation (1.33). Since my production function is estimated at the two-digit industry level, I supplement my analysis with \(\gamma_{cic2,t}\), which controls for any time-varying changes at the two-digit industry level that may confound the results.\(^{42}\) The coefficients of interest are \(\gamma_O\) and \(\gamma_I\).\(^{43}\) Intuitively, these coefficients are identified by comparing the differential changes of the outcome variable across firms, within the same location-by-year and cic2-by-year group. These firms differ only in their differential exposure to changes in tariffs at four-digit (or three-digit) industry level. Across all the specifications, standard errors are clustered two-way, at firm-level and industry-by-year level.

In my baseline estimate, equation (1.39) is estimated with the OLS method. Although there is a large set of fixed-effects included in equation (1.39), there still might be an endogeneity concern of the industry-level tariff changes. Recall that, in my theoretical analysis, productivity is a key determinant of firm-level labor market power. When China joined

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\(^{42}\)This additional fixed-effect term turns out to be important, since I observe some diverging trends in measured distortions and productivity at the 2-digit industry level.

\(^{43}\)An essential assumption for identification of the causal impact of tariff changes on the labor market distortion using equation (1.39) is the constant treatment effect assumption, in which I assume that the causal effects of tariffs are constant across firm, location, industry and time.
the WTO in 2001, it is possible that the Chinese government selectively reduced tariffs for certain industries based on their past productivity growth trends. If this is indeed the case, differences in labor market distortion of firms across industry might be attributable to industry-specific growth in productivity rather than being caused by differential tariff changes. I address this endogeneity concern by following the identification approach in Brandt et al. (2017). Specifically, for the post-WTO period (after 2001), I use the maximum binding tariff negotiated (and fixed) in 1999 as an instrumental variable for the actual applied tariff, and estimate equation (1.39) with the 2SLS method. This instrument alleviates the policy endogeneity concern because it is presumably difficult for Chinese policymakers to correctly predict the productivity evolution of various industries in the post-WTO period and negotiate the maximum tariff levels accordingly. In what follows, my preferred quantitative interpretation is based on the IV estimates, which are more conservative in all of my specifications.

Table 1.5 reports the estimation results. Columns (1) and (2) show the results of the regression equation (1.39), using the (log) overall distortion measured in section 1.3 as the dependent variable. Across the two columns, which use two alternative estimation methods, i.e. OLS and IV, the sign and the significance of the coefficients estimated are consistent with the predictions of theory in propositions (2) and (3). The coefficients of the output tariff have a negative sign, while the input tariff coefficient has a positive sign. In other words, the results show that a reduction in the output tariff increases the labor market distortion, while a reduction in the input tariff leads to a decrease in the measured distortion. Quantitatively, however, only input tariffs have strong and significant impact on the distortion. Specifically, a one percentage point decrease in input tariffs leads to a 0.72 percentage point reduction in the distortion, based on the OLS estimates. IV estimates imply a 0.58 percentage point decrease in the distortion. Combining with the actual change in the input tariffs during my sample period, in which the input tariffs decreased from 11% to 6% on average from 1998-2007, these estimation results suggest that the average labor market distortion decreased
about 2.9% as a consequence of China’s reduction in the input tariffs. Compared with the
effect of input tariffs, output tariff reductions had negligible and insignificant effects on labor
market distortion.

Columns (3) and (4) estimate equation (1.39) using the (log) share-dependent distortion
measured by the reduced-form approach in section 1.4 as the dependent variable. The goal of
these columns is to compare the results between the two different measures of labor market
distortion. Consistent with the results in columns (1)-(2), estimated coefficients for tariffs
have the same signs. In columns (3)-(4), however, the coefficients of both tariffs are strongly
significant, with the reduction in input tariffs having a much stronger effect. Across the two
columns, a one percentage point decrease in output tariffs leads to a 0.016 percentage point
increase in the share-dependent distortion in the OLS estimates, compared to an estimated
0.019 in the IV estimates. On the other hand, a one percentage point decrease in the input
tariffs leads to a 0.093 and 0.123 percentage point decrease in the share-dependent distortion
respectively in the OLS and IV estimates. Taken together and combined with actual tariff
changes during the sample period 1998-2007, columns (3) and (4) suggest that the output
tariff reduction led to a 0.133% increase in the distortion, while the input tariff reduction
led to a 0.62% decrease in the distortion (using IV estimates).

Overall, the empirical results in this section confirm predictions in propositions (2) and
(3) about the impact of a tariff liberalization on firm-level labor market distortion. Across
all specifications, my preferred estimates suggest that even though lowering output tariffs has
a tendency to increase the distortion, its effect is small. On the other hand, lowering input
tariffs substantially reduces the labor market distortion, with the magnitude of the overall
effect about 2.9%. These results hold robustly when using the alternative reduced-form
measure of endogenous distortion in section 1.4.
1.6 Conclusion

This paper studies the impact of international trade policy on competition in the labor market. The paper makes three contributions. First, I develop a tractable model to study the impact of trade policy on distortions in the labor market, providing clear predictions based on this model. Second, I propose two complementary strategies to consistently measure labor market distortion and show that the magnitude of this distortion can be large, contradicting a critical assumption in many trade models that the labor market is perfectly competitive. Third, I establish a causal relationship between trade policy and the endogenous labor market distortion. A key takeaway is that opening up to import competition through lowering output tariffs potentially increases the distortion in the labor markets. On the other hand, lowering input tariffs can substantially decrease the distortion by allowing firms to access cheaper foreign inputs. The proposed operating mechanism of such effects is the endogenous entry and exit of firms across local labor markets induced by trade shocks.

My theoretical and empirical results have a number of implications for our understanding of how trade policy affects labor market performance. Since labor market power has consequential effects on wages, employment, labor shares and inequality, my results suggest that trade can affect the labor market power of firms and thus, alters the labor market outcomes through this mechanism. Even though the context of my empirical analysis is a developing country, i.e. China, it is plausible that this mechanism also operates in developed economies. A fruitful direction for future research is thus to analyze my results’ generalizability to a developed country context. Furthermore, as endogenous distortion accounts for a major part of overall labor market distortion, my results suggest that standard welfare calculations of trade, notably as in Arkolakis, Costinot and Rodriguez-Clare (2012), might be affected by the presence of such distortion and its endogenous response to trade.

There are several important caveats to my analysis. My results concern the measurement of labor market distortion and the causal impact of trade policy on such distortion, yet are silent about its aggregate implications as well as counterfactual welfare impacts when there
are changes in the trade policy regime. Additionally, difficulties can arise in quantitative applications of the model because of the nonlinearity and the existence of multiple equilibria in oligopsony context. Finally, I do not make claims on the relationship between trade, labor market distortion and inequality. I leave these considerations for future research.
Figure 1.1: Exogenous versus Endogenous Distortion in the Labor Market

Note: The figure illustrates the exogenous versus the endogenous features of the labor market distortion. Panel A (left) shows the effect of the exogenous distortion that acts as a uniform “labor tax” ($\chi^x$) on all firms within a local labor market. Panel B (right) shows the effect of the endogenous distortion ($\chi^f_i$) that varies with firm’s size.
Figure 1.2: Distribution of the Labor Market Distortion ($\tilde{\chi}_i$)

Note: The figure illustrates the histogram (left) and kernel density (right) of the measured labor market distortion ($\tilde{\chi}_i$) from production function estimation. The left panel shows the distribution of distortion across all firm-year observations. No distortion cutoff is where $\tilde{\chi}_i = 1$. The right panel displays the evolution of distortion distribution over three equidistant years: 1999, 2003, 2007.
Figure 1.3: Labor Market Distortion ($\tilde{\chi}_i$) and Industry Characteristics (in 2004)

Note: The figure illustrates the correlations between the measured labor market distortion ($\tilde{\chi}_i$) and (2-digit) industry characteristics in 2004. The industry characteristics include: export share, state ownership (SOE) share, female employment share and high-skill employment ratio. High-skill employment ratio is defined as the ratio between high-school and secondary-school degree workers. The figure is based on the data in 2004, because this is the only year that the employment composition information is available.
Figure 1.4: Labor Supply Elasticity by Local Labor Market Wage-bill Share

Note: The figure illustrates the labor supply elasticity ($\eta(s_{ijit})$) as a function of local labor market share in equation (1.36), with the estimated parameters obtained from regression equation (1.33). $p3$ and $p97$ are the 3rd and 97th percentiles, with the values of 1.16 and 2.36 respectively.
Figure 1.5: Distribution of the Endogenous Distortion ($\tilde{\chi}^e(s_{ijkl})$)

Note: The figure is a counterpart of Figure 1.2, but for the endogenous distortion ($\tilde{\chi}^e(s_{ijkl})$) rather than the overall distortion ($\tilde{\chi}_i$). The left panel shows the distribution of distortion across all firm-year observations. The right panel displays the evolution of distortion distribution over three equidistant years: 1999, 2003, 2007.
Figure 1.6: Endogenous Distortion ($\tilde{\chi}(s_{ijlt})$) and Industry Characteristics (in year 2004)

Note: The figure is a counterpart of Figure 1.3, but for the endogenous distortion ($\tilde{\chi}(s_{ijlt})$) rather than the overall distortion ($\tilde{\chi}(i)$). It shows the correlations between the measured endogenous distortion ($\tilde{\chi}(s_{ijlt})$) and (2-digit) industry characteristics in 2004. The industry characteristics include: export share, state ownership (SOE) share, female employment share and high-skill employment ratio. High-skill employment ratio is defined as the ratio between high-school and secondary-school degree workers. The figure is based on the data in 2004, because this is the only year that the employment composition information is available.
Figure 1.7: Tariff Changes versus Initial Tariffs from 2000 (Pre-WTO) to 2007 (Post-WTO) across Industries

Note: The figure illustrates tariff changes against initial tariff levels from 2000 (Pre-WTO) to 2007 (Post-WTO) across industries.
Table 1.1: Revenue Elasticities and Labor Market Distortion by Industry

<table>
<thead>
<tr>
<th>Industry</th>
<th>Capital</th>
<th>Labor</th>
<th>Material</th>
<th>RTS Mean</th>
<th>RTS Median</th>
<th>No. Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>13. Food Processing</td>
<td>0.05</td>
<td>0.07</td>
<td>0.75</td>
<td>0.87</td>
<td>2.99</td>
<td>75778</td>
</tr>
<tr>
<td>14. Food Production</td>
<td>0.07</td>
<td>0.07</td>
<td>0.73</td>
<td>0.87</td>
<td>1.73</td>
<td>25439</td>
</tr>
<tr>
<td>15. Beverage</td>
<td>0.08</td>
<td>0.08</td>
<td>0.70</td>
<td>0.86</td>
<td>2.24</td>
<td>14498</td>
</tr>
<tr>
<td>16. Tobacco</td>
<td>0.10</td>
<td>0.10</td>
<td>0.70</td>
<td>0.89</td>
<td>2.33</td>
<td>261</td>
</tr>
<tr>
<td>17. Textile</td>
<td>0.06</td>
<td>0.08</td>
<td>0.76</td>
<td>0.91</td>
<td>1.79</td>
<td>115777</td>
</tr>
<tr>
<td>18. Garments</td>
<td>0.05</td>
<td>0.11</td>
<td>0.75</td>
<td>0.91</td>
<td>1.49</td>
<td>54948</td>
</tr>
<tr>
<td>19. Leather</td>
<td>0.05</td>
<td>0.10</td>
<td>0.75</td>
<td>0.90</td>
<td>1.71</td>
<td>28192</td>
</tr>
<tr>
<td>20. Timber</td>
<td>0.07</td>
<td>0.09</td>
<td>0.74</td>
<td>0.90</td>
<td>2.26</td>
<td>25140</td>
</tr>
<tr>
<td>21. Furniture</td>
<td>0.05</td>
<td>0.11</td>
<td>0.75</td>
<td>0.91</td>
<td>2.09</td>
<td>14436</td>
</tr>
<tr>
<td>22. Paper-making</td>
<td>0.06</td>
<td>0.09</td>
<td>0.76</td>
<td>0.92</td>
<td>2.19</td>
<td>42029</td>
</tr>
<tr>
<td>23. Printing</td>
<td>0.08</td>
<td>0.07</td>
<td>0.74</td>
<td>0.89</td>
<td>1.35</td>
<td>14624</td>
</tr>
<tr>
<td>24. Cultural</td>
<td>0.05</td>
<td>0.10</td>
<td>0.76</td>
<td>0.91</td>
<td>1.40</td>
<td>16147</td>
</tr>
<tr>
<td>25. Petroleum Processing</td>
<td>0.09</td>
<td>0.09</td>
<td>0.73</td>
<td>0.91</td>
<td>3.75</td>
<td>6414</td>
</tr>
<tr>
<td>26. Raw Chemical</td>
<td>0.07</td>
<td>0.06</td>
<td>0.75</td>
<td>0.88</td>
<td>2.05</td>
<td>87669</td>
</tr>
<tr>
<td>27. Medical</td>
<td>0.09</td>
<td>0.08</td>
<td>0.70</td>
<td>0.87</td>
<td>2.15</td>
<td>24615</td>
</tr>
<tr>
<td>28. Chemical Fibre</td>
<td>0.07</td>
<td>0.07</td>
<td>0.78</td>
<td>0.92</td>
<td>1.77</td>
<td>3428</td>
</tr>
<tr>
<td>29. Rubber</td>
<td>0.07</td>
<td>0.07</td>
<td>0.74</td>
<td>0.88</td>
<td>1.55</td>
<td>13997</td>
</tr>
<tr>
<td>30. Plastic</td>
<td>0.07</td>
<td>0.08</td>
<td>0.76</td>
<td>0.91</td>
<td>1.83</td>
<td>55530</td>
</tr>
<tr>
<td>31. Nonmetal Products</td>
<td>0.07</td>
<td>0.07</td>
<td>0.73</td>
<td>0.87</td>
<td>1.25</td>
<td>109209</td>
</tr>
<tr>
<td>32. Processing of Ferrous</td>
<td>0.07</td>
<td>0.11</td>
<td>0.76</td>
<td>0.94</td>
<td>3.90</td>
<td>25248</td>
</tr>
<tr>
<td>33. Processing of Nonferrous</td>
<td>0.06</td>
<td>0.07</td>
<td>0.76</td>
<td>0.90</td>
<td>2.90</td>
<td>16197</td>
</tr>
<tr>
<td>34. Metal Products</td>
<td>0.07</td>
<td>0.07</td>
<td>0.76</td>
<td>0.90</td>
<td>1.48</td>
<td>59290</td>
</tr>
<tr>
<td>35. Ordinary Machinery</td>
<td>0.08</td>
<td>0.07</td>
<td>0.74</td>
<td>0.89</td>
<td>1.52</td>
<td>85996</td>
</tr>
<tr>
<td>36. Special Equipment</td>
<td>0.07</td>
<td>0.08</td>
<td>0.73</td>
<td>0.88</td>
<td>1.66</td>
<td>41495</td>
</tr>
<tr>
<td>37. Transport Equipment</td>
<td>0.07</td>
<td>0.09</td>
<td>0.75</td>
<td>0.91</td>
<td>1.77</td>
<td>51499</td>
</tr>
<tr>
<td>39. Electric Machinery</td>
<td>0.07</td>
<td>0.07</td>
<td>0.76</td>
<td>0.91</td>
<td>1.79</td>
<td>68908</td>
</tr>
<tr>
<td>40. Electronic and Telecom</td>
<td>0.07</td>
<td>0.10</td>
<td>0.74</td>
<td>0.91</td>
<td>1.67</td>
<td>31385</td>
</tr>
<tr>
<td>41. Measuring Instruments</td>
<td>0.06</td>
<td>0.09</td>
<td>0.73</td>
<td>0.88</td>
<td>1.38</td>
<td>13606</td>
</tr>
<tr>
<td>42. Art Work</td>
<td>0.05</td>
<td>0.09</td>
<td>0.74</td>
<td>0.88</td>
<td>1.41</td>
<td>19214</td>
</tr>
</tbody>
</table>

All Industry | 0.07 | 0.08 | 0.75 | 0.89 | 1.87 | 1.33 | 1140969 |

Note: The table reports estimates of the revenue elasticities of factors (capital, labor, material), the revenue return to scale (RTS), and the measured overall distortion ($\tilde{\chi}_i$) from production function estimation in section 1.3. Except for the distortion, all other statistics are the mean of respective distributions. The table trims observations above and below the 1$^{st}$ and 99$^{th}$ percentiles. The last column reports the number of observations for each two-digit industry. Notice that the RTS would not be equal to 1 in this case because it contains markups. If I impose the constant RTS assumption of the physical production function, the average markup of Chinese manufacturing sector is about 12%.
Table 1.2: Labor Market Distortion and Firm Characteristics

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>$\hat{X}_i$ (1)</th>
<th>$\hat{X}_i$ (2)</th>
<th>$\hat{X}_i$ (3)</th>
<th>$\hat{X}_i$ (4)</th>
<th>$\hat{X}_i$ (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Productivity (TFP)</td>
<td>5.187***</td>
<td>5.442***</td>
<td>5.496***</td>
<td>5.529***</td>
<td>5.836***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Employment</td>
<td>-0.377***</td>
<td>-0.348***</td>
<td>-0.351***</td>
<td>-0.416***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Exporting</td>
<td>-0.315***</td>
<td>-0.274***</td>
<td>-0.184***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foreign-Owned</td>
<td>-0.251***</td>
<td>-0.158***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOE</td>
<td>0.028***</td>
<td>0.045***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HHI (Employer Concentration)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.087***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>Minimum Wage (Monthly)</td>
<td>-0.002***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations: 1,140,969 1,140,969 1,140,969 1,140,969 912,972
R-squared: 0.350 0.390 0.396 0.398 0.430
Industry FEs: Yes Yes Yes Yes Yes
Year FEs: Yes Yes Yes Yes Yes

Note: The table reports the regression results of the measured distortion ($\hat{X}_i$) on firm-level characteristics. The HHI in column (5) is the Herfindahl-Hirschman Index of employer concentration within a prefecture. Minimum wage data (at prefecture-level) is only available from 2000-2007, therefore there are less observations in column (5). Fixed effects are denoted as FEs. Robust standard errors are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.5$, *** $p < 0.01$. 
Table 1.3: Wage and Employment Response to the US-China TPU Demand Shock

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>( \log(w_{i,t+1}) )</th>
<th>( \log(L_{i,t+1}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>( \tau_{jt}^{TPU} )</td>
<td>-0.066***</td>
<td>-0.073***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Market Share ( (s_{ijlt}) \times \tau_{jt}^{TPU} )</td>
<td>0.059***</td>
<td>0.195***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Market Share ( s_{ijlt} )</td>
<td>0.015***</td>
<td>0.189***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,140,969</td>
<td>766,851</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.709</td>
<td>0.733</td>
</tr>
<tr>
<td>Firm FEs</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Location-Year FEs</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Clustered Two-way</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: The table reports the results of regression equation (1.33) with two dependent variables: \( \log(w_{i,t+1}) \) and \( \log(L_{i,t+1}) \). Market Share \( s_{ijlt} \) is the local (prefecture) labor market wage-bill share, defined in equation (1.35), and \( \tau_{jt}^{TPU} \) is the trade policy uncertainty (TPU) shock. Columns (2) and (4) have less observations because of the use of lagged share. Fixed effects are denoted as FEs. Standard errors in parentheses are clustered two-way, at firm level and industry-by-year level. Significance levels: * \( p < 0.1 \), ** \( p < 0.5 \), *** \( p < 0.01 \).
Table 1.4: China’s Tariffs Evolution from 1998-2007

<table>
<thead>
<tr>
<th>Year</th>
<th>Output Tariff ($\tau^O$)</th>
<th>Input Tariff ($\tau^I$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average (1)</td>
<td>Std. Deviation (2)</td>
</tr>
<tr>
<td>1998</td>
<td>0.16</td>
<td>0.09</td>
</tr>
<tr>
<td>1999</td>
<td>0.16</td>
<td>0.09</td>
</tr>
<tr>
<td>2000</td>
<td>0.16</td>
<td>0.09</td>
</tr>
<tr>
<td>2001 (WTO)</td>
<td>0.15</td>
<td>0.08</td>
</tr>
<tr>
<td>2002</td>
<td>0.12</td>
<td>0.07</td>
</tr>
<tr>
<td>2003</td>
<td>0.11</td>
<td>0.07</td>
</tr>
<tr>
<td>2004</td>
<td>0.10</td>
<td>0.06</td>
</tr>
<tr>
<td>2005</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>2006</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>2007</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>Total</td>
<td>0.12</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Note: All tariffs are computed as the natural log of 1 plus the ad valorem tariffs i.e. $\ln(1 + \tau)$. Input tariffs are computed as weighted averages of output tariffs, using input shares from China’s Input-Output table in 2002 as weights.
Table 1.5: Impact of Tariff Changes on the Labor Market Distortion

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Nonparametric</th>
<th>Parametric</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>log((\tilde{\chi}_{ijlt}))</td>
<td>log((\tilde{\chi}^e(s_{ijlt})))</td>
</tr>
<tr>
<td></td>
<td>OLS IV</td>
<td>OLS IV</td>
</tr>
<tr>
<td></td>
<td>(1) (2)</td>
<td>(3) (4)</td>
</tr>
<tr>
<td>Output Tariffs ((\tau^O_{j,t-1}))</td>
<td>-0.039</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Input Tariffs ((\tau^I_{j,t-1}))</td>
<td>0.720**</td>
<td>0.577*</td>
</tr>
<tr>
<td></td>
<td>(0.291)</td>
<td>(0.318)</td>
</tr>
<tr>
<td>Observations</td>
<td>958,663</td>
<td>958,663</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.758</td>
<td>0.764</td>
</tr>
<tr>
<td>Firm FEs</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Location-Year FEs</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Clustered Two-way</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: The table reports the results of regression equation (1.39) with two dependent variables: log(\(\tilde{\chi}_{ijlt}\)) and log(\(\tilde{\chi}^e(s_{ijlt})\)). All tariffs are measured as the natural log of 1 plus the ad valorem tariffs i.e. ln(1 + \(\tau\)). Instruments for the applied tariffs (after 2001) are the maximum tariffs negotiated before China’s accession to WTO. Observations with negative values of the labor supply elasticity measured in section 1.4 are excluded. Fixed effects are denoted as FEs. Standard errors in parentheses are clustered two-way, at firm level and industry-by-year level. Significance levels: * \(p < 0.1\), ** \(p < 0.5\), *** \(p < 0.01\).
Appendices

1.A  Theory Appendix

1.A.1  Derivations of the Endogenous Distortion

Equation (1.14) is derived in several steps. First, the endogenous distortion can be expressed as:

\[ \tilde{\chi}(z) = 1 + \chi(z) = \frac{MRPL(z)}{w(z)} = 1 + \frac{1}{\eta(z)}, \]  
(A1)

where \( \eta(z) \) is the elasticity of labor supply curve facing firm \( z \). Formally:

\[ \frac{1}{\eta(z)} = \frac{d\log(w(z))}{d\log(L(z))}. \]  
(A2)

Second, notice that it is straightforward to rewrite the labor supply system in (11)-(12) in inverse form as:

\[ w(z) = L(z)^{\frac{1}{\eta}}L^{\frac{1}{\theta}} - \frac{1}{\eta} \Lambda', \]  
(A3)

where \( L = \left[ \sum_{z \in Z} L(z)^{\frac{\eta + 1}{\theta}} \right] \) as in equation (1.7) and \( \Lambda' \) is another exogenous aggregate labor supply index. Next, taking the log of the inverse labor supply curve:

\[ \log(w(z)) = \frac{1}{\eta} \log(L(z)) + \left( \frac{1}{\theta} - \frac{1}{\eta} \right) \log L + \log \Lambda'. \]  
(A4)
Taking the derivative, I obtain:

\[
\frac{d \log(w(z))}{d \log(L(z))} = \frac{1}{\eta} + \left(\frac{1}{\theta} - \frac{1}{\eta}\right) \frac{d \log(L)}{d \log(L(z))}. \tag{A5}
\]

Now, note that \( \log(L) = \frac{\eta}{\eta+1} \log[\sum_{z \in Z} L(z)^{\frac{\eta+1}{\eta}}] \). Thus, :

\[
\frac{d \log(L)}{d \log(L(z))} = \frac{\eta}{\eta+1} L^{\frac{\eta+1}{\eta}} \frac{\eta+1}{\eta} L(z)^{\frac{\eta+1}{\eta}} = \left(\frac{L(z)}{L}\right)^{\frac{1}{\eta}} \left(\frac{L(z)}{L}\right) \tag{A6}
\]

Combine with the fact that \( \left(\frac{L(z)}{L}\right)^{\frac{1}{\eta}} = \frac{w(z)}{W} \) (see also in Berger, Herkenhoff and Mongey (2019)) in this labor supply system, we have:

\[
\frac{d \log(L)}{d \log(L(z))} = \frac{w(z)L(z)}{WL} = s_z. \tag{A7}
\]

Combine (A1), (A5), and (A7), I obtain the results in equation (1.14).

### 1.A.2 Profit Monotonicity

The profit monotonicity condition is stated as follows:

\[
\Pi^K(z^{(k)}) \geq \Pi^{K+1}(z^{(k)}) \geq \Pi^{K+1}(z^{(k+1)}). \tag{A8}
\]

**Proof:** The second inequality is proved first. This inequality states that, given the same market condition, more productive firms always have more profit than less productive firms (recall the productivity ranking \( z^{(1)} > ... > z^{(k)} > z^{(k+1)} \)). The proof is by deduction: the more product firm \( z^{(k)} \) can always charge at least the same price as the less productive firm \( z^{(k+1)} \) and makes more profit. (Q.E.D)

The first inequality states that for the same firm with productivity \( z^{(k)} \), the firm is more profitable if there are less competitors in the local labor market, i.e. removing the firm \( z^{(k+1)} \).
from the market. To show this, let’s first rewrite the profit of firm \( z \) as:

\[
\Pi(z) = Az^{\frac{n-1}{n}}L(z)^{\frac{n-1}{n}} - L(z)^{\frac{n+1}{n}} \left( \left[ \sum L(z')^{\frac{n+1}{n}} \right]^{\frac{1}{n+1}} \right)^{\frac{n}{n+1}},
\]

(A9)

where \( A = P^{\frac{n-1}{n}}I^{\frac{1}{n}} \) summarizes the aggregate condition in product market, exogenous to the firm. It is straightforward to show that:

\[
\frac{\partial \Pi(z)}{\partial L(z')} \leq 0 \quad \text{and} \quad \frac{\partial^2 \Pi(z)}{\partial L(z)\partial L(z')} \leq 0.
\]

(A10)

The left inequality asserts that lower employment on the part of a local competitor increases profit of firm \( z \). This is because lower \( L(z') \) reduces the wage of firm \( z' \), and thus allow firm \( z \) to set lower wage. The right inequality asserts that lower employment of a local competitor induces firm \( z \) to increases its employment. These are typical properties of the Cournot competition environment.

From (A10), by removing firm \( z^{(k+1)} \) and essentially makes its employment \( L(z^{(k+1)}) \to 0 \), all incumbent firms in the market becomes more profitable, and hence, \( \Pi^K(z^{(k)}) \geq \Pi^{K+1}(z^{(k)}) \). (Q.E.D)

1.A.3 Proposition 1

Given the equilibrium selection rule based on productivity ranking in (18) and the profit monotonicity condition in (20), it can be shown that a unique equilibrium \( K^* \) exists. \( K^* \) also fully characterizes all firm-level variables.

Proof: Suppose there exists two values \( K_1 \) and \( K_2 (K_1 < K_2) \) in this environment that satisfy the equilibrium selection rule. By equilibrium definition we have:

\[
\Pi^{K_1}(z^{(K_1)}) \geq 0 > \Pi^{K_1+1}(z^{(K_1+1)}) \quad \text{and} \quad \Pi^{K_2}(z^{(K_2)}) \geq 0 > \Pi^{K_2+1}(z^{(K_2+1)})
\]

(A11)

Nonetheless, by productivity ranking, we must have: \( z^{(K_1+1)} \geq z^{(K_2)} \) since \( K_1 < K_2 \). Com-
bine with the profit monotonicity condition proved in section 1.A.2, we must have:

\[ 0 > \Pi^{K_1+1}(z^{(K_1+1)}) \geq \Pi^{K_2}(z^{(K_2)}) \geq 0. \]  \tag{A12}

This condition clearly cannot hold. Therefore the equilibrium \( K^* \) is unique. From (A9), and given the set of firm productivities, \( K^* \) determines all firm-level variables in equilibrium. \( \text{(Q.E.D)} \)

### 1.A.4 Proposition 2

Proposition 2 states three main results: \( K^*(\tau^O) \geq 0, \) and for \( z \geq z^{(k^*)}, s'(\tau^O,.) \leq 0, \tilde{\chi}'(\tau^O,.) \leq 0. \)

I first prove that \( K^*'(\tau^O) \geq 0. \) Recall from equation (1.22) that \( P'(\tau^O) \geq 0, \) because lower output tariff increases competition and decreases the aggregate price. Plug this condition into equation (A9), it is straightforward to see that \( \Pi'(\tau^O,.) \geq 0 \) for all \( z, \) holding the labor market condition constant. Suppose there exists two alternative scenarios of trade policy environment \( \tau_1^O > \tau_2^O, \) such that \( K^*(\tau_1^O) \equiv K_1^* < K^*(\tau_2^O) \equiv K_2^*. \)

Consider the firm \( z^{(K_1+1)}. \) By the equilibrium definition in proposition 1, we must have \( \Pi^{K_1}(z^{(K_1+1)}) < 0 \) and \( \Pi^{K_2}(z^{(K_1+1)}) \geq 0. \) Notice also that from the profit monotonicity condition, we must have \( \Pi^{K_2}(z^{(K_1+1)}) \leq \Pi^{K_1}(z^{(K_1+1)}). \) Combine these inequalities, we have:

\[ \Pi^{K_1}(z^{(K_1+1)}) < 0 \leq \Pi^{K_2}(z^{(K_1+1)}) \leq \Pi^{K_1}(z^{(K_1+1)}). \]  \tag{A13}

Expressions in (A13) clearly can not hold. Therefore, it must be true that as \( \tau_1^O > \tau_2^O, \) then \( K^*(\tau_1^O) \equiv K_1^* \geq K^*(\tau_2^O) \equiv K_2^*. \) \( \text{(Q.E.D)} \)

Second, to show that for all incumbent firms \( z \geq z^{(K^*)}, \) the local labor market share \( s'(\tau^O,.) \leq 0 \) and endogenous distortion \( \tilde{\chi}'(\tau^O,.) \leq 0, \) labor market share can be rewritten
as:

\[ s_z^{K^*} = \frac{L^{K^*}(z)^{\frac{\eta + 1}{\eta}}}{\sum_{z \in Z^{K^*}} L^{K^*}(z')^{\frac{\eta + 1}{\eta}}}. \]  
(A14)

Consider again \( \tau_1^O > \tau_2^O \), we know that \( K_1^* \geq K_2^* \). I will show that \( s_z^{K^*_1}(\tau_1^O) = s_z^{K^*_1}(\tau_2^O) \leq s_z^{K^*_2}(\tau_2^O) \). In plain words, the first equality states that in this environment, holding fixed the number of firms in the local labor market, the aggregate sectoral condition has no effect on the local labor market share of firms, and thus, on the endogenous distortion.\(^{44}\) The second inequality states that holding the aggregate condition unchanged, the firm \( z \) has a bigger market share if there are fewer competitors in the labor market. The first equality is the key to this proof. To show that the first equality holds, I rewrite the FOC of firm’s problem with respect to labor as follow:

\[ \mathbf{A}(\tau^O)(\frac{\gamma - 1}{\gamma} \frac{\eta}{\eta + 1})z^{\frac{\eta - 1}{\eta}} = L(z)^{\frac{1}{\eta + \frac{1}{\gamma}}} L_1[1 + \Gamma L(z)^{\frac{\eta + 1}{\eta}}], \]  
(A15)

where \( \mathbf{A}(\tau^O) = \mathbf{P}(\tau^O)^{\frac{\eta - 1}{\eta}} \mathbf{I}^{\frac{1}{\gamma}} \) and \( L = [\sum L(z')^{\frac{\eta + 1}{\eta}}] \) and \( \Gamma = (\frac{\eta}{\eta + 1})(\frac{1}{\gamma} - \frac{1}{\eta}) \). Combine the FOCs of each firm in equation (A8), for any value of \( \tau^O \), we have a system of \( K^* \) equations with \( K^* \) variables \( L(z^{(1)}), ..., L(z^{(K^*)}) \).

Plug into (A15) the values of \( \tau_1^O \) and \( \tau_2^O \), and holding \( K^* \) fixed, we have two systems of equations \( \forall z \in Z^{K^*} \):

\[ \mathbf{A}(\tau_1^O)(\frac{\gamma - 1}{\gamma} \frac{\eta}{\eta + 1})z^{\frac{\eta - 1}{\eta}} = L_1(z)^{\frac{1}{\eta + \frac{1}{\gamma}}} L_1[1 + \Gamma L_1(z)^{\frac{\eta + 1}{\eta}}], \]  
(A16)

and

\[ \mathbf{A}(\tau_2^O)(\frac{\gamma - 1}{\gamma} \frac{\eta}{\eta + 1})z^{\frac{\eta - 1}{\eta}} = L_2(z)^{\frac{1}{\eta + \frac{1}{\gamma}}} L_2[1 + \Gamma L_2(z)^{\frac{\eta + 1}{\eta}}], \]  
(A17)

Let \( \frac{\mathbf{A}(\tau_1^O)}{\mathbf{A}(\tau_2^O)} \equiv \lambda \frac{1}{\eta + \frac{1}{\gamma}} \). Notice that the system (A16) and (A17) are two isomorphic systems of equations, meaning that each equation in system (A17) is scaled by a factor \( \lambda \frac{1}{\eta + \frac{1}{\gamma}} \) of

\(^{44}\)MacKenzie (2018) circumvents this problem by allowing firms to have variable markups, but holding fixed the number of active firms. My solution is to allow for firms’ endogenous entry and exit to affect the local labor market share.
a respective equation in system (A16). It follows that if \( \{L(z)|z \in Z^{K^*}\} \) is a solution to system (A17), then it must be true that \( \{\lambda L(z)|z \in Z^{K^*}\} \) is a solution to system (A16) and inversely. The system of equations in (A15)-(A17) in principle can have multiple solutions due to its nonlinearity. Therefore, I assume that a unique and stable solution exists and focus only on this solution. Since any \( L(z) \) is scaled by a constant factor \( \lambda \) under the two alternative tariff scenarios, the local labor market share expressed in (A14) would remain unchanged. As a result, we have \( s_{z}^{K^*_1}(\tau^O_1) = s_{z}^{K^*_2}(\tau^O_2) \).

To show that \( s_{z}^{K^*_1}(\tau^O_2) \leq s_{z}^{K^*_2}(\tau^O_2) \), recall the second inequality from (A10). From this condition, we know that when the number of competitors decreases and holding the aggregate condition fixed, incumbent firms have incentives to increase employment, taking extra labor of the firm that do not operate under \( K^*_2 \) environment (\( L^{K^*_2}(z) \geq L^{K^*_1}(z) \)).

Further more, when there are less firms operate in the market, the aggregate labor index is smaller (\( \sum_{z \in Z^{K^*_2}} L^{K^*_2}(z')^{\frac{n+1}{\eta}} \leq \sum_{z \in Z^{K^*_1}} L^{K^*_1}(z')^{\frac{n+1}{\eta}} \)). Combine these two inequalities, we have \( s_{z}^{K^*_1}(\tau^O_2) \leq s_{z}^{K^*_2}(\tau^O_2) \). As market share changes, the distortion changes in the same direction, following directly from equation (1.14). (Q.E.D)

1.A.5 Proposition 3

The proof for proposition 3 follows straightforwardly from the proof for proposition 2. The only difference now is that the impact of input tariff is magnified by \( \frac{1-\alpha}{\alpha} \), the relative factor shares between labor and intermediate input.

To see this, notice that change in input tariff \( \tau^I \) affects the competition in the labor market through a similar channel as output tariff \( \tau^O \), that is they both affect the labor demand \( MRPL \). Therefore, all arguments in the proof for proposition 2 apply. The goal is now to show that the effect of input tariff on the competition in the labor market could be much larger than that of output tariff, especially if the production uses intermediate input heavily. From the production function in equation (1.22), I can derive the \( MRPL \) of firm \( z \)
as:

\[ MRPL(z) = z \alpha L(z)^{\alpha-1} M(z)^{1-\alpha}. \]  \hspace{1cm} (A18)

From equation (A18), conditional on the same amount of labor \( L(z) \), change in labor demand is determined by:

\[ d \log(MRPL(z)) = (1 - \alpha) d \log(M(z)). \]  \hspace{1cm} (A19)

From the FOC condition of firm \( z \) with respect to \( M(z) \), I obtain:

\[ d \log(M(z)) = \frac{1}{\alpha} d \log(1 + \tau^I). \]  \hspace{1cm} (A20)

Combine (A19) and (A20), change in labor demand as a result of change in input tariff is:

\[ d \log(MRPL(z)) = -\frac{1 - \alpha}{\alpha} d \log(1 + \tau^I). \]  \hspace{1cm} (A21)

Equation (A21) concludes the proof for proposition 3. (Q.E.D)

1.B Production Function Estimation

This section provides supplementary notes for production function estimation procedure in section 1.3. In particular I provide the detailed derivations of firm’s profit maximization problem, timing assumptions as well as the moment conditions for the second GMM stage. A firm maximizes its profit with respect to material input conditional on its information set in period \( t \), denoted by \( \mathbb{I}_t \) as follow:

\[ \max_{M_t} \mathbb{E}[F(k_t, l_t, m_t) * e^{(\omega_t + \varepsilon_t)\mathbb{I}_t}] - p_{M_t} M_t, \]  \hspace{1cm} (B1)

where \( F(\cdot) \) and \( M_t \) are the exponential counterparts of \( f(\cdot) \) and \( m_t \) in equation (1.26) respectively. \( p_{M_t} \) is the price of material, taken as given by the firm. Taking FOC of this problem
yields:
\[ \frac{\partial}{\partial M_t} F(k_t, l_t, m_t)e^{\omega_t} E[e^{\varepsilon_t}] - p_{M_t} = 0. \] (B2)

Taking the log version of the above equation, I obtain:
\[
\log(s^{M}_t) \equiv \log \left( \frac{p_{M_t} M_t}{R_t} \right) = \log E[e^{\varepsilon_t}] + \log \frac{\partial}{\partial m_t} f(k_t, l_t, m_t) - \varepsilon_t \\
= \log \frac{\partial}{\partial m_t} f(k_t, l_t, m_t) - \varepsilon_t. 
\] (B3)

The second equality of (B3) (also equation (1.27)) follows under the assumption that \( E[e^{\varepsilon_t}] = 1 \) or \( E[\varepsilon_t] = 0 \). In my empirical implementation, I estimate \( \hat{\varepsilon}_t \) and correct for any asymmetry in the measurement error \( \varepsilon_t \) (see also in Gandhi, Navarro and Rivers (2017)). In the Chinese firm-level data, the estimated \( \hat{\varepsilon}_t \) exhibits little asymmetry and requires minimum correction, i.e. \( E[e^{\hat{\varepsilon}_t}] \approx 1 \) for most industries.

In what follows, \( v_t \) is a vector of additional state variables that I control for, including year, location, industry, firm’s ownership, export status and tariff levels. The timing assumptions of the GNR productivity model is as follows:

- At the end of period \((t-1)\), the firm chooses \((k_t, l_t, v_t)\) and whether to exit at \(t\).
- At the beginning of period \(t\), \( \eta_t \) (and hence \( \omega_t \)) realizes. The firm observes their productivity for period \(t\).
- The firm optimally chooses \( m_t \), after which \( \varepsilon_t \) realizes and completely determines \( r_t \).
- At the end of \(t\), the firm chooses \((k_{t+1}, l_{t+1}, v_{t+1})\) and whether to exit at \(t+1\), repeating the same process.
The moment conditions for the second GMM stage are:

\[ E \left[ \eta_t \otimes \begin{bmatrix} 1 \\ \Psi_{t-1} \\ C_t(.) \\ C_{t-1}(.) \end{bmatrix} \right] = 0 \]  

(B4)

1.C Data Construction and Filtering

The China’s Annual Survey of Industrial Enterprises (ASIE) data record firms’ balance sheets information and contain a firm-specific identifier (ID). Firms could change ID over time due to various reasons (e.g. due to M&A activity). I match firms over the years in the sample first based on their IDs. After matching on IDs, I match firms based on name, zip code, telephone number, and legal person representatives concurrently.

In my final sample, I drops all firms with missing or negative values of the main variables, including revenue, fixed assets, employment, material, wage-bill. To maintain consistent thresholds throughout the sample, I drop all firms that employ fewer than 8 workers or firms that have revenue less than 5 million Renminbi (RMB). Since my production function estimation is at two-digit industry level, I drop all firms that switch 2-digit industry to avoid complex selection bias of production function estimation due to firms switching two-digit industry. This procedure reduces 18% of firm-year observations. I further drop all firms outside the 1\(^{st}\) and 99\(^{th}\) percentiles of revenue, fixed assets, employment, material, wage-bill. This procedure shrinks the data by 5 percentage point. My cleaning procedures are similar to standard practices in the literature that uses ASIE data, see for example Brandt, Biesebroeck and Zhang (2014) and Brandt et al. (2017).
1.D Additional Figures and Tables

Figure A1: Changes in Tariffs over Time (Pre-Post WTO)

Note: The figure illustrates changes in the average and interquartile range of applied tariffs (AHS) across 6-digit HS industries over time (pre-post WTO).
Figure A2: Applied Tariffs (AHS) versus Binding Tariffs (BND)

Note: The figure illustrates changes in the (average) applied tariffs (AHS) and binding tariffs (BND) over time.
Figure A3: Convergence of Applied Tariffs (AHS) to Binding Tariffs (BND) across Industries and Years

Note: The figure illustrates changes in the applied tariffs (AHS) and binding tariffs (BND) across industries after WTO accession. The base year is 2000.
Table A1: Aggregate Summary Statistics of the Chinese Firm-level Data

<table>
<thead>
<tr>
<th>Year</th>
<th>No. of Firms</th>
<th>VA</th>
<th>Sales</th>
<th>Output</th>
<th>Employment</th>
<th>Export</th>
<th>Fixed Assets (Net)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>165118</td>
<td>1.94</td>
<td>6.54</td>
<td>6.77</td>
<td>56.44</td>
<td>1.08</td>
<td>4.41</td>
</tr>
<tr>
<td>1999</td>
<td>162033</td>
<td>2.16</td>
<td>7.06</td>
<td>7.27</td>
<td>58.05</td>
<td>1.15</td>
<td>4.73</td>
</tr>
<tr>
<td>2000</td>
<td>162882</td>
<td>2.54</td>
<td>8.37</td>
<td>8.57</td>
<td>53.68</td>
<td>1.46</td>
<td>5.18</td>
</tr>
<tr>
<td>2001</td>
<td>171256</td>
<td>2.83</td>
<td>9.19</td>
<td>9.54</td>
<td>54.41</td>
<td>1.62</td>
<td>5.54</td>
</tr>
<tr>
<td>2002</td>
<td>181557</td>
<td>3.30</td>
<td>10.86</td>
<td>11.08</td>
<td>55.21</td>
<td>2.01</td>
<td>5.95</td>
</tr>
<tr>
<td>2003</td>
<td>196220</td>
<td>4.20</td>
<td>13.95</td>
<td>14.23</td>
<td>57.48</td>
<td>2.69</td>
<td>6.61</td>
</tr>
<tr>
<td>2004</td>
<td>279092</td>
<td>6.62</td>
<td>19.78</td>
<td>20.17</td>
<td>66.22</td>
<td>4.05</td>
<td>7.97</td>
</tr>
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<td>2005</td>
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<td>69.31</td>
<td>4.77</td>
<td>8.95</td>
</tr>
<tr>
<td>2006</td>
<td>301961</td>
<td>9.11</td>
<td>31.08</td>
<td>31.66</td>
<td>73.49</td>
<td>6.05</td>
<td>10.58</td>
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<td>2007</td>
<td>336768</td>
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<td>39.76</td>
<td>40.51</td>
<td>78.75</td>
<td>7.34</td>
<td>12.34</td>
</tr>
</tbody>
</table>

Note: The table reports the aggregate summary statistics of the Chinese firm-level data, prior to cleaning procedures. Employment is in millions of workers. All monetary values are denoted in trillions Renminbi (RMB).
### Table A2: Revenue Elasticities and Labor Market Distortion by Industry (ACF-Translog)

<table>
<thead>
<tr>
<th>Industry</th>
<th>Capital</th>
<th>Labor</th>
<th>Material</th>
<th>$\tilde{\chi}_i$ (Mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td>13. Food Processing</td>
<td>0.19</td>
<td>0.19</td>
<td>.</td>
<td>6.94</td>
</tr>
<tr>
<td>14. Food Production</td>
<td>0.21</td>
<td>0.19</td>
<td>.</td>
<td>3.58</td>
</tr>
<tr>
<td>15. Beverage</td>
<td>0.21</td>
<td>0.06</td>
<td>.</td>
<td>1.23</td>
</tr>
<tr>
<td>16. Tobacco</td>
<td>0.39</td>
<td>0.33</td>
<td>.</td>
<td>3.10</td>
</tr>
<tr>
<td>17. Textile</td>
<td>0.22</td>
<td>0.21</td>
<td>.</td>
<td>3.50</td>
</tr>
<tr>
<td>18. Garments</td>
<td>0.14</td>
<td>0.35</td>
<td>.</td>
<td>3.16</td>
</tr>
<tr>
<td>19. Leather</td>
<td>0.17</td>
<td>0.26</td>
<td>.</td>
<td>2.86</td>
</tr>
<tr>
<td>20. Timber</td>
<td>0.25</td>
<td>0.25</td>
<td>.</td>
<td>4.68</td>
</tr>
<tr>
<td>21. Furniture</td>
<td>0.14</td>
<td>0.34</td>
<td>.</td>
<td>4.73</td>
</tr>
<tr>
<td>22. Paper-making</td>
<td>0.23</td>
<td>0.21</td>
<td>.</td>
<td>4.24</td>
</tr>
<tr>
<td>23. Printing</td>
<td>0.19</td>
<td>0.08</td>
<td>.</td>
<td>1.03</td>
</tr>
<tr>
<td>24. Cultural</td>
<td>0.16</td>
<td>0.26</td>
<td>.</td>
<td>2.80</td>
</tr>
<tr>
<td>25. Petroleum Processing</td>
<td>0.25</td>
<td>0.19</td>
<td>.</td>
<td>4.75</td>
</tr>
<tr>
<td>26. Raw Chemical</td>
<td>0.23</td>
<td>0.13</td>
<td>.</td>
<td>2.71</td>
</tr>
<tr>
<td>27. Medical</td>
<td>0.27</td>
<td>0.15</td>
<td>.</td>
<td>2.60</td>
</tr>
<tr>
<td>28. Chemical Fibre</td>
<td>0.33</td>
<td>0.19</td>
<td>.</td>
<td>5.22</td>
</tr>
<tr>
<td>29. Rubber</td>
<td>0.19</td>
<td>0.10</td>
<td>.</td>
<td>1.55</td>
</tr>
<tr>
<td>30. Plastic</td>
<td>0.20</td>
<td>0.22</td>
<td>.</td>
<td>3.81</td>
</tr>
<tr>
<td>31. Nonmetal Products</td>
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<td>0.04</td>
<td>.</td>
<td>0.47</td>
</tr>
<tr>
<td>32. Processing of Ferrous</td>
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<td>0.26</td>
<td>.</td>
<td>7.13</td>
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<tr>
<td>33. Processing of Nonferrous</td>
<td>0.22</td>
<td>0.20</td>
<td>.</td>
<td>5.79</td>
</tr>
<tr>
<td>34. Metal Products</td>
<td>0.21</td>
<td>0.19</td>
<td>.</td>
<td>2.93</td>
</tr>
<tr>
<td>35. Ordinary Machinery</td>
<td>0.19</td>
<td>0.12</td>
<td>.</td>
<td>1.72</td>
</tr>
<tr>
<td>36. Special Equipment</td>
<td>0.16</td>
<td>0.14</td>
<td>.</td>
<td>1.87</td>
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<tr>
<td>37. Transport Equipment</td>
<td>0.25</td>
<td>0.27</td>
<td>.</td>
<td>4.32</td>
</tr>
<tr>
<td>39. Electric Machinery</td>
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<td>0.23</td>
<td>.</td>
<td>4.05</td>
</tr>
<tr>
<td>40. Electronic and Telecom</td>
<td>0.21</td>
<td>0.35</td>
<td>.</td>
<td>4.83</td>
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<tr>
<td>41. Measuring Instruments</td>
<td>0.13</td>
<td>0.13</td>
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<td>1.28</td>
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<tr>
<td>42. Art Work</td>
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<td>0.17</td>
<td>.</td>
<td>1.73</td>
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<tr>
<td><strong>All Industry</strong></td>
<td>0.21</td>
<td>0.20</td>
<td>.</td>
<td>3.40</td>
</tr>
</tbody>
</table>

**Note:** This table reports estimates of the revenue elasticities of factor inputs: capital and labor, and the measured *overall distortion* ($\tilde{\chi}_i$), using the translog production function estimation procedure in Ackerberg, Caves and Frazer (2015) (ACF). All statistics are the mean of respective distributions. The ACF method assumes that production function is Leontief, i.e. perfect complementarity between material and other factors. The table trims observations above and below the 1st and 99th percentiles.
Bibliography


Chapter 2

Trade, Labor Markets, and Intergenerational Mobility in Vietnam

(joint work with Devashish Mitra and Beyza Ural-Marchand)

2.1 Introduction

Intergenerational mobility refers to the extent to which socioeconomic status is able to change across generations. By many standards, it is a key element of human progress (World Bank (2018)). And yet, while intergenerational mobility has been studied extensively in labor economic literature (see for example Solon (1999), Chetty et al. (2014), Chetty and Hendren (2018b), Chetty and Hendren (2018a)), little is known about the relationship between social mobility across generations, economic development and international trade. Given that globalization has played a major role in promoting economic growth around the world in the past decades, it is important to ask whether international trade, as an external shock, reinforces or breaks down the persistence of socioeconomic status across generations. In this paper, we examine to what extent trade liberalization affects intergenerational mobility in a small but rapidly developing country, Vietnam.

It is noteworthy to first clarify why intergenerational mobility matters. From a the-
oretical perspective, if mobility is impeded by factors such as market imperfections and inefficient social mechanisms, for instance credit market imperfections or caste-based society, greater mobility implies a more efficient allocation of resources. Furthermore, from an empirical perspective, more intergenerational mobility is found to be highly associated with higher economic growth, faster poverty reduction, lower inequality and a more stable society (World Bank (2018)). If mobility is structurally related to these desirable aspects of society, enhancing mobility can have meaningful and long-term impacts on development.

To shed light on the impacts of international trade on intergenerational mobility, we use eight rounds of Vietnam Household Living Standard Surveys (VHLSS) from 2001/2002 to 2015/2016 to measure intergenerational mobility, and exploit a large and exogenous export shock in Vietnam induced by United States-Vietnam Bilateral Trade Agreement (henceforth, BTA) to identify the impacts. This empirical context is ideal to answer our question because Vietnam is a good example of a developing economy that has experienced fast growth as well as many structural changes, while at the same time has benefited immensely from trade openness during this sample period. We focus our attention on occupational mobility as our main dimension of mobility because (1) occupation is likely to be directly related to workers’ welfare through corresponding income and job stability and (2) occupation is reflective of skills, which are influenced by trade. In addition, in the context of a developing country such as Vietnam, having a formal job plays a particularly important role in poverty alleviation and welfare of workers (World Development Report (2006), Emran and Shilpi (2011)).

The US-Vietnam BTA was a major trade shock and has had very large impacts on Vietnam’s trade and economic growth. The BTA took effect in December 2001. Following its implementation, US’s tariffs on their imports from Vietnam decreased from an average of more than 23% to about 2.5%. The BTA tariff reductions were large and allowed Vietnam immediate access to the large and prolific US market. An attractive feature of the BTA shock

\[^{1}\text{In Emran and Shilpi (2011), Vietnam is considered a “rural” economy with a very large share of workers in the agriculture sectors. As will be clear in section 2.2, this is indeed the case. Even until 2016, 44.53\% of workers are in farm-related sectors.}\]
is that the US’s tariff reductions for Vietnam were plausibly exogenous (McCaig (2011), McCaig and Pavcnik (2018)). We therefore exploit the BTA tariff reductions to identify the impact of trade shocks on intergenerational mobility in our analysis.

Our analysis in this paper delivers three key contributions to the current literature on trade and intergenerational mobility. First, we find that the BTA has raised occupational mobility by about 5.11 percentage points, accounting for almost one-third of overall increase in mobility in Vietnam during our sample period from 2002 to 2016. The effect of the BTA is larger in the long-run than in the short-run. Second, we show that the BTA might have also worked through higher educational attainment of younger generations i.e. sons. Finally, we also show that both improvements in Vietnam’s export value overall as well as unit-value in particular are channels through which the BTA affects occupational mobility.

Related Literature

Our paper is related to the broad literature on trade, labor markets and inequality. Most closely related to our paper is a paper by Ahsan and Chatterjee (2017) in which they study the impact of trade liberalization on intergenerational occupational mobility in India. Ahsan and Chatterjee (2017) is the very first study that examines international trade as a potential determinant of mobility. They find that following India’s trade liberalization in 1991, sons living in the urban districts with greater exposure to trade liberalization are more likely to have better occupations as compared to their fathers. Our findings in this paper are different from their findings in three important ways. First, our paper focuses on the impacts of export liberalization due to tariff reductions by a trading partner, in this case the US, rather than import competition liberalization by the home country. Second, in terms of methodology, multiple rounds of household survey data permit a difference-in-difference (DID) research design and allow us to examine the short- and long-run effects of trade shocks. In contrast, Ahsan and Chatterjee (2017) only use cross-sectional variations in their empirical strategy. Finally, we are able to purge a link between improvements in both exports and unit-value
(proxied for quality) on skill demand and mobility. These differences allow us to make new contributions to the scant literature on trade and intergenerational mobility.

The literature on trade and inequality has provided empirical evidence that even though trade is beneficial overall, it can raise inequality (Verhoogen (2008), Helpman et al. (2017)). In most of these studies, the main empirical interest is cross-sectional (horizontal) inequality. Similar to Ahsan and Chatterjee (2017), we show that trade liberalization can nevertheless promote equality of opportunities by improving intergenerational mobility and reduce inequality along this (vertical) dimension.

Methodologically, our paper is related to a large literature on trade and labor market that employs local labor market approach. In particular, we measure trade exposure following Hasan, Mitra and Ural (2007), Topalova (2010), McCaig (2011), Autor, Dorn and Hanson (2013) and Kovak (2013). This empirical approach has an advantage in that it is grounded in the specific-factors model of local economies as shown in Autor, Dorn and Hanson (2013) and Kovak (2013).\(^2\) We adopt this approach in our analysis in which the units of local labor market are provinces and central cities in Vietnam.\(^3\)

The paper is organized as follows. In section 2.2, we describe our Vietnam household survey data and provide descriptive analyses of the labor market in Vietnam during our sample period from 2002 to 2016. Section 2.3 describes how we measure intergenerational occupational mobility and several patterns of mobility in Vietnam. Section 2.4 summarizes background on Vietnam’s international trade. In sections 2.5 and 2.6, we estimate the impact of the BTA on mobility and explore its mechanisms. Section 2.7 concludes.

\(^2\)In the general economics literature, this local labor market approach dates back to Bartik (1991).

\(^3\)Provinces and central cities are equivalent administrative units in Vietnam. To simplify the narrative, we use provinces to represent both the actual provinces and central cities in this paper.

Before analyzing changes in intergenerational mobility, we characterize main features of Vietnam’s labor market during our sample period from 2001/2002 to 2015/2016 using Vietnam Household Living Standard Surveys (VHLSS) data. This section first describes the household survey data and then provides descriptive statistics regarding trends in labor market’s demographic characteristics, occupational and sectoral structures, which eventually helps us to purge a link between changes in overall labor market conditions and intergenerational mobility.

2.2.1 Household Survey Data

Our main data source are Vietnam Household Living Standard Surveys (VHLSS) from 2001/2002 to 2015/2016, which are representative and implemented biennially by Vietnam’s General Statistics Office (GSO). The stated goals of VHLSSs are to “monitor systematically the living standard of Vietnam’s societies” and to “exercise the monitoring and assessment of the implementation of the Comprehensive Poverty Alleviation and Growth Strategy defined in Country Strategy Paper approved by the Government Prime Minister” (The World Bank (2015)).\(^4\) VHLSSs contain rich information on household- and individual-level demographics, employment, household expenditures, health and other aspects. We use the demographics and employment modules in this paper. For each VHLSS round, the recall period for expenditures and employment modules is 12-month, meaning that answers to questionnaire refer to what happens during the most recent 12-month period.\(^5\) Whenever suitable, we also

\(^4\)On top of that, VHLSSs also “serve the evaluation of realization of the Millennium Development Goals and the Socio-economic Development Goals set out by Vietnamese Government” (see also in The World Bank (2015)). These surveys are designed and implemented with the technical assistance from UNDP and the World Bank.

\(^5\)This detail is important for our subsequent analyses on the impacts of the BTA because the BTA came to force in December 2001. This means that VHLSS 2001/2002 captures information in the pre-BTA period. See also McCaig (2011) and McCaig and Pavcnik (2018).
utilize data from the Vietnam Living Standards Survey (VLSS) for 1997/1998, which is a predecessor of VHLSS.\footnote{There are some differences in terms of sample size and level-of-detail in questionnaire between VLSS and VHLSS. Most notably, VLSSs cover much fewer households (6000 for VLSS 1997/1998). In addition, the number of household interviewed appears to be biased towards urban/rural areas for many provinces in the VLSS 1997/1998. See also the Data Appendix and McCaig (2011) for details and some other issues.}

Table 2.1 provides main summary statistics of our datasets. In all rounds of VHLSS, almost 45000 households are interviewed. However, due to current data restrictions from Vietnam’s GSO, we only have access to samples of about 30000 households for 2001/2002 round and 9000 households for 2011/2012 round. Breaking down by urban-rural criterion, the fraction of households in urban areas increases over time, from 23\% in 2002 to 30\% in 2016. Furthermore, the average household size decreases significantly over time, from about 4.5 heads per household in 2002 to 3.8 heads per household in 2016. In terms of individuals in the sample, the fraction of male and female remains relatively balanced, with the share of male individuals of about 50\% across years. In what follows, we break down further several demographic characteristics with a particular focus on workers participating in the labor market drawn from the sample.

**2.2.2 Demographic Characteristics of Employed Workers**

We restrict our sample of employed workers to individuals with age between 16 and 64, who are also at the time participating in the labor market. Figure 2.1 illustrates the average age and education levels of workers stratified by gender and urban/rural status. The top panels indicate that female workers are on average older than male workers over the sample period. Furthermore, the average age of employed workers increase substantially, from about 35.2 and 35.6 in 2002 to 39.5 and 40.2 in 2016, respectively for male and female workers. From the top right panel of Figure 2.1, male workers on average achieve higher education level than female workers. However, in contrast to age, the average education level increases less, from about 7.4 and 6.8 in 2002 to 8.3 and 7.8 in 2016, respectively for male and female workers.
The bottom panels of Figure 2.1 indicate that urban workers are relatively order and more educated as compared to rural workers. The age structure of urban versus rural workers is perhaps interesting. Over the sample period from 2002 to 2016, we also observe significant increases in the average age of employed workers in both urban and rural areas. In addition, the average age of rural workers appears to catch up with urban workers by 2016. Similar to the top right panel, we do not see much increase in the average education level of workers in both urban and rural areas. Nevertheless, the education gap between urban and rural is large and remains so over the sample period from 2002 to 2016.

2.2.3 Sectoral and Occupational Structures

During the period from 2002 to 2016, there are several significant changes in the structure of Vietnam’s labor market. In this subsection, we focus the allocation of workers across sectors and occupations over time.

Table 2.2 illustrates the allocation of workers across broad economic sectors over time. As shown in Table 2.2, the four dominant sectors of Vietnam’s economy during our sample period are: Agriculture, Manufacturing, Construction, and Services (combined). This structure remains relatively stable with the largest change happens in agriculture sector. In particular, from 2002 to 2016, employment share of agriculture sector decreases 14.98 percentage points, from 59.51% to 44.53%. This decrease in agricultural employment share is reallocated towards all other sectors, with manufacturing experiencing a 4.37 percentage points increase in share, up from 11.25% in 2002 to 15.62% in 2016. Construction sector sees a 2.66 percentage points increase in share while the rest is allocated to service sector. Overall, we observe a large movement in share of workers out of agriculture during this sample period. This resonates with the findings of McCaig and Pavcnik (2013) using Census Data in 1989, 1999, 2009 and other aggregate data sources. McCaig and Pavcnik (2013) document workers moving out of agriculture from 1990 to 2008 as a major structural change in Vietnam’s labor market and show that this movement has contributed to the high aggregate
labor productivity growths in Vietnam during this period.

Table 2.3 illustrates the allocation of workers across 10 broad categories of occupation over time. These broad categories include: (0) Army, (1) Leaders in All Fields and Levels, (2) High-level Professionals in All Fields, (3) Mid-level Professionals in All Fields, (4) Elementary Professionals (Staff & White-collar Personnel), (5) Skilled Workers in Services, (6) Skilled Workers in Agriculture, Sylviculture, Aquaculture, (7) Skilled Handicraftsmen & Other Skilled Manual Workers, (8) Assemblers and Machine Operators, (9) Unskilled Workers. Classification of these 10 broad categories are based on occupation codes recorded in the VHLSSs. This 1-digit classification is also designed such that it is consistent with the International Standard Classification of Occupations (ISCO-08) proposed by the International Labour Organization (International Labour Organization (2012)).

Table 2.3 shows that Vietnamese economy’s employment during our sample period is also largely dominated by unskilled occupations. In 2002, more than 75% of workers are categorized as unskilled. By 2016, this share decreases significantly by 19.31 percentage points to 56.51%. Nevertheless, unskilled workers still account for more than half of all employed workers. Over time, unskilled workers are reallocated mainly to jobs including Mid-level Professionals (3.42 percentage points), Skilled Handicraftsmen & Other Skilled Manual Workers (4.68 percentage points) and Assemblers and Machine Operators (4.63 percentage points). Large increases are also observed in shares of Skilled Workers in Services (2.42 percentage points) and Skilled Workers in Agriculture, Sylviculture, Aquaculture (3.01 percentage points). Table 2.3 demonstrates clearly how Vietnam’s occupation structure evolves over time, moving workers out of unskilled and towards more skilled jobs.

\[7\] VHLSSs record occupation codes at a more disaggregate 2-digit level. We observe some concordance issues at 2-digit level between VHLSS rounds before and after 2010. Therefore, we use 1-digit occupation level as our main point of reference. Table A4 in the Appendix provides the allocation of workers across 2-digit occupations recorded in VHLSSs.
2.2.4 Wages and Inequality

Between 2002 and 2016, real annual wages increase from an average of 5.5 million VNDs to 16.8 million VNDs, a three-fold increase.\(^8\) Figure 2.2 illustrates the wage disparities between male and female workers, as well as between urban and rural workers, over our sample period.

The top right panel shows that female workers earn consistently less than male workers and the gender wage gap appears to enlarge over time in absolute terms. From 2002 to 2016, male workers’ wages increase from an average of 5.8 million VNDs to 17.8 million VNDs. For female workers, wages increase from an average of 5.0 million VNDs to 15.4 million VNDs. As a result, the gender wage gap increases from 0.8 million VNDs to 2.4 million VNDs in absolute terms. However, in relative terms, male workers get paid 16\% higher than their female counterparts in 2002. This premium decreases slightly to 15.5\% in 2016. As shown in the top left panel, relative gender wage inequality remains mostly unchanged during this period, reflecting that economic development has not been associated with gender pay equality in Vietnam.

The bottom right panel shows that urban workers also earn higher wages as compared to rural workers. From 2002 to 2016, urban workers’ wages increase from an average of 8.9 million VNDs to 20.5 million VNDs. For rural workers, wages increase from an average of 4.0 million VNDs to 14.4 million VNDs. Even though, the urban-rural wage gap appears to increase in absolute terms, from 4.9 million VNDs in 2002 to 6.1 million VNDs in 2016, such gap has narrowed down in relative terms. As shown in the bottom left panel, the urban-rural wage gap has decreased dramatically, from 122.5\% to 42\% wage premium during this period. This pattern is consistent with the urban-rural wage convergence in India, but is in contrast with China’s experience as documented by Hnatkovska and Lahiri (2019).

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\(^8\)Real wages are deflated using Consumer Price Index series from the World Bank. The base year is 2002. In 2016, Vietnam’s CPI is 302. VND is the acronym for Vietnam Dong.
2.3 Intergenerational Mobility

To investigate the degree of intergenerational mobility, we narrow our focus to a sample comprised of sons and fathers within households. Following Hnatkovska, Lahiri and Paul (2013) and Ahsan and Chatterjee (2017) for India, we abstract from studying mobility among female members of households because working-age female members’ labor market outcomes tend to be correlated with the decision to co-reside with biological parents in Vietnam, which we cannot control for based on information in the VHLSSs. In contrast, coresident rate is much higher for adult sons due to Vietnam’s cultural values. As mentioned in section 2.1, we also focus on intergenerational occupational mobility as our main outcome of interest. As a result, our sample is restricted to son-father pairs in which both members are contemporarily participating in the labor market. Our final working sample is comprised of sons aged between 16 and 40 since the majority of working sons in our sample are within this range. Furthermore, fathers of sons aged above 40 are also more likely to have retired, which can potentially bias our subsequent analyses.

Our first task is to construct a ranking of occupations. Conceptually, we generally think of a “good job” as containing a high level of skill intensity. Ideally, we would like a task-based measure of skill intensity for each occupation, similar to Autor, Levy and Murnane (2003) and Acemoglu and Autor (2011). Unfortunately, this information is not readily available for Vietnam’s occupations. Our baseline measure of skill intensity is therefore based on information about the average education level of workers within each occupation, similar to the ranking approach in Ahsan and Chatterjee (2017). Specifically, for each 1-digit occupation in Table 2.3, we construct an education index $EI_o$ as follow:

$$ EI_o = \sum_i \left( \frac{w_i}{\sum_k w_k} \right) \times Edu_i. $$  

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9Using a 2011 nationally representative survey dataset of elderly parents of age 60 and above, Teerawichitchainan, Pothisiri and Long (2015) document that 41% of parents live with their adult sons while only 26% of parents live with their adult daughters.

10Since we use occupation codes at 1-digit aggregate level, we do have rankings based on task-based measures. We present some of these results in the Appendix.
In equation (2.1), $w_i$ and $w_k$ are individual $i$ and $k$'s sample weights in VHLSS 2001/2002 (base year). $Edu_i$ is grade level completed by individual $i$. The weighted summation is performed across all individuals within occupation $o$.\(^{11}\) Here, we use our full sample of workers aged between 16 and 64 to compute the education index in equation (2.1) to ensure the representativeness of the index. Table 2.4 illustrates our education index and ranking results.

From Table 2.4, the top occupation category is (2) High-level Professionals in All Fields with an education index of 11.9, meaning almost everyone in this category has a high school degree. This category includes jobs such as scientists, high-level experts in technical fields and high-level experts in life and health sciences. As expected, the subsequent categories are (3) Mid-level and (4) Elementary Professionals with education indices of 11.4 and 11.1 respectively. (1) Leaders in All Fields and Levels has an index of 10.8. The next group of occupations are (8) Assemblers and Machine Operators, (5) Skilled Workers in Services and (7) Skilled Handicraftsmen & Other Skilled Manual Workers with education indices indicating that most workers completed secondary schooling. The final group comprises of (9) Unskilled Workers and (6) Skilled Workers in Agriculture, Sylviculture, Aquaculture. Interestingly, the education indices suggest that average education of unskilled workers is slightly higher than skilled workers in agriculture, which are 6.6 and 6.5 respectively. Since the majority of unskilled workers in category (9) are in agriculture, we assign the same bottom rank for these two occupation categories.\(^{12}\) This assignment is consistent with the notion that mobility out of agriculture provides workers access to better jobs in nonfarm sectors, which is an important avenue to gain stable income streams and escape poverty (World Development Report (2006), Emran and Shilpi (2011)).\(^{13}\)

\(^{11}\)Slightly different from Ahsan and Chatterjee (2017), we have detail information about grade completed by each individual rather than indicators for degree received in VHLSSs. This will distinguish, for example, workers who complete grade 8 versus workers who complete grade 5 only. One disadvantage of our data is that we do not have detail 3-digit level occupation codes as in India’s context.

\(^{12}\)See also the employment share of occupation code (92) Unskilled Workers in Agriculture, Forestry and Aquaculture in Table A4 in the Appendix.

\(^{13}\)This assignment is also consistent with a major structural change in Vietnam during our sample period associated with workers moving out of agriculture sectors as documented in McCaig and Pavcnik (2013).
Based on our ranking of occupations, we construct an indicator variable of upward occupational mobility $Upward_i$. In particular, this indicator equals 1 if son $i$ works in a higher-ranked occupation than his father and equals 0 otherwise.

$$Upward_i = \begin{cases} 
1 & \text{if } \text{Rank}(\text{Son}) > \text{Rank}(\text{Father}) \\
0 & \text{otherwise.}
\end{cases}$$

(2.2)

Figure 2.3 illustrates the persistence of upward occupational mobility for all years in our sample. The top panel shows the distribution of son’s occupation conditioning on being born to fathers with top occupation (High-level Professionals) while the bottom panel shows the same distribution conditioning on being born to fathers with bottom occupation (Unskilled and Agricultural Workers). The top panel suggests that more than 50% of sons being born to fathers who are high-level professionals also become high-level professionals. On the other hand, 73% of sons being born to fathers who are unskilled and agricultural workers also become unskilled and agricultural workers, as shown in the bottom panel of Figure 2.3. Overall, Figure 2.3 indicates a very high correlation of occupational choice across generations in the VHLSS sample.

This high level of intergenerational occupational persistence masks important underlying changes in social mobility over time. Figure 2.4 illustrates the evolution of upward occupational mobility from 2002 to 2016. In 2002, less than 15% of sons had better jobs than their fathers. Nonetheless, this fraction has increased consistently. By 2010, about 24% of sons are able to move up the ranking, and by 2016, this fraction increases to about 32.5%. Figure 2.4 implies that there has been a substantial increase in upward occupational mobility. We are interested in investigating how much of this increase in mobility can be attributed to the US-Vietnam Bilateral Trade Agreement. In the next sections, we describe the background of the US-Vietnam BTA in details and explore its implications for intergenerational mobility in Vietnam during this period.
2.4 Background on Vietnam’s International Trade

2.4.1 United States-Vietnam Bilateral Trade Agreement (BTA)

The United States-Vietnam Bilateral Trade Agreement (BTA) took about five years to negotiate and entered into force in December 2001. The trade agreement was negotiated following the formal normalization of diplomatic relations between US and Vietnam since 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. Even though, Vietnam also committed to cut tariffs for 250 out of more than 6,000 HS-6 US products, the average tariff reductions are negligible since Vietnam already applied its low MFN tariffs to US before the BTA.

Upon being granted NTR/MFN status, Vietnam was moved from the “Column 2” to “Column 1” (MFN) of the US tariff schedule. Importantly, although the BTA is subjected to a lengthy negotiation process on both sides, the magnitude of US tariff changes to Vietnam is largely predetermined and not influenced by either US or Vietnam’s bargaining position. In particular, the “Column 2” tariffs are the tariffs assigned to nonmarket economies under the Smoot-Hawley Tariff Act of 1930. On the other hand, the MFN tariffs are the tariffs offered to all WTO members by the US and determined through a multilateral bargaining process with other countries long before 2001. To this extend, the BTA tariff reductions

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14 The primary sources of information for the description of the BTA in this section are STAR-Vietnam (2003) and McCaig (2011).
15 80% of these 250 tariff concessions was in the agriculture sector.
16 Upon China’s accession to WTO in 2001, China also experienced a similar treatment from US, which is exogenous in US and China’s industries’ perspectives. However, in the case of China, such treatment is interpreted as a removal of trade policy uncertainty rather than an actual trade policy change. See also
of U.S to Vietnam are plausibly exogenous to any domestic conditions or political processes of Vietnam (see also exogeneity arguments in McCaig (2011), Fukase (2013), McCaig and Pavcnik (2018)).

The BTA tariff reductions are also large in magnitude. Following the BTA, the ad valorem US tariffs to Vietnam’s products decrease from an average of 23.4% to 2.5%. The decrease is largest for the manufacturing sector, from an average of 33.8% to 3.6% and is much more modest for the agriculture and other primary sectors. As we will show next, the BTA was followed by large and immediate changes in Vietnam’s exports to US.

2.4.2 Vietnam’s Exports to US

We document two most salient features of Vietnam’s exports to U.S during the past two decades following the BTA: (1) exports has increased substantially and consistently and (2) export structure swiftly shifts to much higher unit-value products.\(^{17}\)

Figure 2.5 illustrates Vietnam’s export value to US from 1996 to 2016. Prior to the BTA, exports to US was about 1.04 billion US dollars, accounted 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 US grew to 2.6 billion US dollars, a 147% increase. By 2006, annual exports to US amounted to 9.2 billion US dollars, a nine-fold increase, and accounted for 23% of total exports and almost 14% of GDP.\(^{18}\) By 2016, Vietnam exported 43.6 billion US dollars to US, which represented 20% of total exports and almost 21% of GDP.\(^{19}\) Figure 2.5 also shows that the bulk of increase in Vietnam’s exports to US is manufacturing. Specifically, the share of manufacturing exports increased from an average of 40% prior to the BTA to around 67% in 2002 and 87% in 2006 respectively. By 2016, this share was 92%.

A parallel and significant change in Vietnam’s exports to US following the BTA is a

\(^{17}\)All values in this subsection are in nominal term.

\(^{18}\)See Figure A4 in the Appendix where we zero in on the changes in period from 1996-2006 and shows a sharp increase in exports following the BTA.

\(^{19}\)By this time, Vietnam was able to diversify its export portfolio with second- and third-largest export partners being China and Japan respectively.
sharp increase in average unit value of exports. Figure 2.6 illustrates the average unit value of Vietnam’s exports to US from 1996 to 2016. From 1996 to 2001, the average unit value almost did not change and remained at around 15 US dollars per unit. In 2002, the average unit value increased to 33 US dollars per unit, a double increase. Unit value continued to increase and by 2006, it reached 52 US dollars per unit. The unit value remained about at the same level for almost ten years and only increased again to about 65 US dollars per unit since 2012. If unit value partially represents the quality of export products, Figure 2.6 suggests that export quality of Vietnam’s products has increased substantially during this period. In subsequent empirical analyses, we show that tariff reductions following the BTA is the key underlying determinant driving the improvements in both Vietnam’s exports and export quality to US.

2.4.3 WTO Accession in 2007

During the period from 2002 to 2016, Vietnam implemented another major trade reform following its accession to WTO in January 2007. Accession to WTO was a lengthy process and Vietnam had been preparing for this event by implementing reforms on three major fronts: (1) administrative procedure, (2) gradual removal of trade barriers, and (3) conformation of their legal system to international trade law. For our purpose, we focus on the removal of tariffs during Vietnam’s accession to WTO period.

Upon WTO accession, Vietnam immediately cut average tariffs by about 3 percentage points across all industries. Figure 2.7 illustrates Vietnam’s average applied tariffs from 1998-2016. As shown in Figure 2.7, tariffs had already been cut gradually over time before WTO accession. From 1998 to 2007, average tariff decreases from 17.3 percentage points to 13.4 percentage points. In 2008, average tariff dropped sharply another 3 percentage points and remained at the level of about 9 percentage points since 2013. Decomposing by

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20Unit value is a weighted average of unit values at HS 10-digit level, with the weights being the export values of each product.

21See Pham (2011) for a brief description of these reforms.
broad sectors, manufacturing tariffs have always been higher while primary sectors’ tariffs have always been lower than the average tariffs. This reflects the country’s comparative advantages and political economy motives in setting the tariffs to protect its manufacturing sectors while at the same time opening up the primary sectors for competition and access to intermediate inputs.

There was much expectation about the beneficial prospects at the time of Vietnam’s WTO accession. Nevertheless, the evidence on such benefits are scant and less conclusive. Pham (2011) and Vo and Nguyen (2009) are among the few studies that examine the economic impacts of Vietnam’s WTO accession. One of the robust findings in both studies is that Vietnam’s imports and inward foreign direct investments (FDI) appear to increase substantially due to the accession, although WTO membership did not have any direct impact on exports. To this end, we control for trade liberalization due to Vietnam’s WTO accession in our analyses since earlier research such as Ahsan and Chatterjee (2017), Hasan, Mitra and Ural (2007), Edmonds, Pavcnik and Topalova (2010) have shown that import liberalization can have important impacts on labor market outcomes in general and intergenerational mobility in particular.

2.5 Impact of BTA on Intergenerational Mobility

A key interest in this paper is to understand how the BTA affected intergenerational mobility in Vietnam from 2002 to 2016. We first briefly describe how we measure households’ exposure to trade shocks associated with the BTA in 2001. We then specify our empirical models used to estimate causal impacts of the BTA exposure on intergenerational mobility.

2.5.1 Measuring the BTA Exposure

We adopt a local labor market approach that widely used in the international trade and labor market literature. In particular, following Hasan, Mitra and Ural (2007), McCaig (2011),
Topalova (2010) and Kovak (2013), we exploit provincial variation in the BTA exposure that arises due to differences in initial industrial structure across provinces. Our measure of provincial exposure is as follows:

\[ \tau_p^{BTA} = \tau_p^{MFN} - \tau_p^{Column 2} < 0, \]  

(2.3)

where \( \tau_p^{BTA} \) is the BTA tariff exposure of province \( p \). \( \tau_p^{MFN} \) and \( \tau_p^{Column 2} \) are the provincial MFN and “Column 2” tariffs respectively, and defined as:

\[ \tau_p^X = \sum_j s_{jp} \times \tau_j^X, \]  

(2.4)

where \( X \in \{MFN, \text{Column 2}\} \) and \( \tau_j^X \) is the respective US tariff for industry \( j \).\(^{22}\) The share \( s_{jp} \) captures the variation in initial industrial structures across provinces and is computed as:

\[ s_{jp} = \frac{\sum_i w_{ijp}}{\sum_{k,m} w_{kmp}}, \]  

(2.5)

where \( w_{ijp} \) and \( w_{kmp} \) are individual weights in the VHLSS 2001/2002. In this equation, \( i, k \) index individual and \( j, m \) index industry. In economic terms, \( s_{jp} \) represents employment share of industry \( j \) within province \( p \) at the beginning of our sample period (pre-BTA).\(^{23}\) Similar to Hasan, Mitra and Ural (2007) and Kovak (2013), but different from McCaig (2011) and Topalova (2010) however, we compute the employment share only within traded industries (scaled exposure) rather than including the non-traded sectors. This empirical approach is grounded in theory as suggested by Kovak (2013).\(^{24}\)

Figure 2.8 illustrates a map of Vietnam’s provinces/central cities with variation in the BTA exposure. In the figure, lighter areas faced smaller BTA tariff cuts, while darker areas

\(^{22}\)All tariffs are measured as natural log of one plus the actual average ad valorem tariffs.

\(^{23}\)As in equation (2.1), we restrict our sample in equation (2.5) to workers aged between 16 and 64 recorded in the VHLSS 2001/2002.

\(^{24}\)Importantly and similar to Kovak (2013), we find that including the non-traded sectors in the BTA exposure computation magnifies our estimates of the effects and make these estimates more significant. The results for this approach are available upon request.
faced larger cuts. Across 63 provinces and central cities, the BTA tariff exposure, measured as provincial tariff reductions in equation (2.3), range from 5.80 percentage points to 27.58 percentage points. The top-4 BTA exposure includes Ho Chi Minh City, Da Nang, Hanoi (and Ha Tay combined) and Binh Duong. The bottom-4 BTA exposure includes Ca Mau, Quang Ninh, Ha Giang and Son La. As is clear from the map, the Red River Delta, Central Coast and Mekong Delta are among the regions that expose the most to the BTA shock.

### 2.5.2 Empirical Strategy - Baseline

To examine the impact of the BTA on intergenerational occupational mobility, we begin with a baseline difference-in-difference (DID) model specified as follows:

\[
Upward_{ipt} = \theta \times PostBTA_t \times \tau_{p}^{BTA} + \gamma \tau_{pt}^{VN} + X'_{ipt}\beta + \lambda_p + \lambda_t + \varepsilon_{ipt}. \tag{2.6}
\]

In equation (2.6), \(Upward_{ipt}\) is an upward mobility indicator of son \(i\) in province \(p\) and year \(t\), defined as in equation (2.2). \(PostBTA_t\) is an indicator variable for post-BTA years. Specifically in our sample, data in the VHLSS 2001/2002 round are treated as pre-BTA while data in the later VHLSS rounds are considered as post-BTA. \(\tau_{pt}^{VN}\) is Vietnam’s tariff of province \(p\) in year \(t\) and defined analogously to \(\tau_{p}^{BTA}\) as in equation (2.4). The inclusion of \(\tau_{pt}^{VN}\) controls for the province-level protection on Vietnam’s side and WTO accession as mentioned in section 2.4. \(X_{ipt}\) is a vector of demographic controls including age, age squared, father’s age, father’s age squared, marriage status, urban status, minority status, household size and share of male members within the household. In addition, similar to Emran and Shilpi (2011) and Ahsan and Chatterjee (2017), we also control for father’s education index.

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\(^25\)Prior to 2003, Vietnam has 61 provinces and central cities. From 2003 to 2008, it splits several provinces into smaller administrative units and increases this number to 64. Since 2008 until now, the number decreases to 63 due to the merge of Hanoi and Ha Tay. See the Data Appendix for the geographic concordances.

\(^26\)As mentioned in section 2.2, the recall period of VHLSSs is 12-month. The BTA entered into force in December 2001. This means that VHLSS 2001/2002 records pre-BTA data. Furthermore, we expect the effect of the BTA on mobility takes time to realize.

\(^27\)In particular, \(\tau_{pt}^{VN} = \sum_j s_{jp} \times \tau_{jt}^{VN}\).
as a proxy for unobservable genetic traits. Whenever suitable, we also add measures of sons’ educational attainment to control for education channel of mobility. $\lambda_p$ and $\lambda_t$ are province and year fixed effects respectively.

From equation (2.6), our identification is obtained by comparing the change in fractions of sons who have experienced upward mobility across provinces before and after the BTA, and who are exposed differentially to the BTA shocks due to initial industrial structures of provinces. Standard errors are clustered at province-year level, which is the level of variation of the BTA shock. Our main parameter of interest is $\theta$, which captures the average effect of the BTA on intergenerational occupational mobility.

Table 2.5 presents our baseline model’s results. Column (1) shows the baseline result without any control. Columns (2) and (3) add the vector of demographic controls and Vietnam’s tariffs progressively. Column (4) adds education controls. Across columns (1)-(4), the estimated effects of the BTA are stable and significant. In particular, the magnitude of the estimates ranges from $-0.418$ to $-0.498$. This suggests that a 1 percentage point decrease in the BTA provincial tariff leads to a $0.418$-$0.498$ point increase in upward occupational mobility. Taking our preferred estimate in column (3) $-0.498$ and combining it with the fact that the average BTA exposure across province is $-10.27$ points, our baseline result suggests that the BTA has induced $5.11$ percentage points increase in upward occupational mobility. This accounts for almost one-third of overall increase in mobility during our sample period from 2002 to 2016. This is one of our key results in this paper.

2.5.3 Extended DID Model

Since we have multiple rounds of VHLSS that span over almost two decades and the BTA occurs in the beginning of our sample period, it is possible to disentangle the short- and long-term effects of the BTA. To this end, we estimate an extended DID model, specified as

\footnote{Recall from section 2.3 that overall mobility increases from 15% in 2002 to 32.5% in 2016.}
follows:

\[
U_{ipt} = \sum_{y=2002}^{2016} \theta_1 y \mathbb{1}\{y = t\} \times \tau_{BTA}^{BTA} + \sum_{y=2002}^{2016} \theta_2 y \mathbb{1}\{y = t\} \times \tau_{VN}^{VN} + X'_{ipt}\beta + \lambda_p + \lambda_t + \varepsilon_{ipt}. \tag{2.7}
\]

In equation (2.7), the effect of \(\tau_{BTA}^{BTA}\) is allowed to vary over time. This heterogeneity is captured by the interactions between \(\tau_{BTA}^{BTA}\) and the year indicators \(\mathbb{1}\{y = t\}\). In this extended DID model, we also control for the WTO accession in a similar manner. In particular, \(\tau_{VN}^{VN}\) is defined as \(\tau_{VN}^{VN} \equiv \tau_{VN}^{y} - \tau_{VN}^{2006}\). This approach effectively normalizes tariffs in 2006 to zero and allows Vietnam’s tariff reductions due to WTO affect mobility differently over time.

Table 2.6 presents our extended model’s results. Column (1) shows the result without WTO controls. Column (2) shows the effects of WTO without the BTA shocks. Column (3) includes both BTA and WTO. Across all columns, we include the vector of demographic controls. From column (1), we observe that the average effect in column (2) of Table 2.5 are decomposed over time. Specifically, the effects of the BTA become larger and more statistically significant over time (except for 2014). In column (2), WTO accession alone does not appear to have large and persistent effects on occupational mobility. Only in 2008, which is one-year after Vietnam’s WTO accession, we see that provinces/central cities more exposed to WTO accession have higher mobility. This is consistent with the findings of Ahsan and Chatterjee (2017) that import competition can induce upward mobility. In column (3), we decompose further the effects of the BTA which might be influenced by the WTO accession. In this column, the effects of the BTA becomes much stronger and more statistically significant while the effects of WTO accession almost disappear. Figure 2.9 illustrates the column (1) (top) and column (3) (bottom) results from Table 2.6. Overall, a robust pattern is that the long-term effects of the BTA are larger than the short-term effects,

\footnote{The effect of year 2002 is normalized to 0 as our base year in this extended DID framework.}

\footnote{Nevertheless, in their empirical context, Ahsan and Chatterjee (2017) study the effects 9 year post-liberalization and they use a cross-sectional variation rather than a DID research design for identification.}
suggesting persistent and long-lasting effects of the BTA on intergenerational occupational mobility. This is our second key result.

2.6 Mechanism

In this section, we explore potential mechanisms through which the BTA affects intergenerational occupational mobility. We consider two mechanisms. First, since better jobs generally require higher level of education, we examine whether sons living in the areas with more exposure to the BTA shocks attain more education. Second, as shown in Figures 2.5-2.6 and discussed in section 2.4, it is possible that BTA-induced improvements in both Vietnam’s exports and unit-value (proxied for quality) have contributed to the mobility. We show that these are indeed the case.

2.6.1 Education Channel

To explore the effect of the BTA on educational attainment of sons within households, we first estimate our extended DID model similar to equation (2.7) with education-related dependent variables:

$$ Edu_{ipt} = \sum_{y=2002}^{2016} \theta_{1y} \mathbb{1}\{y = t\} \times \tau_p^{BTA} + \sum_{y=2002}^{2016} \theta_{2y} \mathbb{1}\{y = t\} \times \tau_y^{VN} + X_{ipt}' \beta + \lambda_p + \lambda_t + \varepsilon_{ipt}. $$

In equation (2.8), $Edu_{ipt}$ is a measure of education level of son $i$ in province $p$ and year $t$. The first three panels of Figure 2.10 illustrate the model results with dependent variables being indicators for completing primary school, secondary school and high school respectively as highest educational accomplishment. These results correspond to column (3) of Table 2.6. From Figure 2.10, sons living in the provinces that expose more to the BTA shocks appear to be less likely finish only primary or secondary school. The decreases in such likelihood
are much stronger for secondary-school completion. On the other hand, sons living in these areas are more likely to obtain a high-school degree. These results suggest that the BTA might have induced sons’ human capital investment through education.

To further link sons’ educational attainment to the intergenerational mobility dimension, we consider a measure of intergenerational educational mobility where mobility is defined as an indicator for sons having a high-school degree but not their fathers. The last panel of Figure 2.10 captures the effects of the BTA on educational mobility. As illustrated in this panel, sons living in areas that expose more to the BTA shocks are more likely completed high school as compared to their fathers. Overall, Figure 2.10 displays a very similar pattern as compared to Figure 2.9 in that the effects of the BTA seem to be increasingly strong and persistent over time.

### 2.6.2 Exports and Unit-Value

Recall that in section 2.5 we have investigated the direct (reduced-form) impact of the BTA tariff reductions on intergenerational occupational mobility. To see how the BTA tariff reductions work through improvements in Vietnam’s exports, we first establish the relationships between the BTA tariff reductions and exports.

We begin by constructing a province-level export index similar to province-level tariffs in equation (2.4). In particular, export index of province \(p\) in year \(t\) is computed as:

\[
EXI_{pt} = \sum_j s_{jp} \times \log(Export_{jt}).
\]  

(2.9)

In equation (2.9), \(\log(Export_{jt})\) is the natural log of exports to US in industry \(j\) and year \(t\). \(s_{jp}\) is the employment share of traded industry \(j\) within province \(p\) drawn from VHLSS 2001/2002 as defined in equation (2.5).

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31 We also find that the BTA shocks decrease downward educational mobility and increase probability of both sons and fathers having high-school degree.

32 This construction ensures that \(dEXI_{pt} = \sum_j s_{jp} \times d\log(Export_{jt})\)
Given this province-level export index, we then estimate how the BTA tariff reductions affect provinces’ exports to US with the following equation:

\[ E X I_{pt} = \sum_{y=1998}^{2016} \theta_{1y} \{ y = t \} \times \tau_{pBTA}^{BTA} + \lambda_p + \lambda_t + \varepsilon_{pt}. \]  

(2.10)

Notice that equation (2.10) is estimated at province level, and since trade data is available before 2001, we could estimate this model for years from 1998 to 2016.\(^{33}\) We also control for province and year fixed effects, and standard errors are clustered two-way at province and year level. Our estimation results are shown in columns (1) and (3) of Table A3 in the Appendix and illustrated in Figure 2.11. As clearly shown in Figure 2.11, the BTA has very large effects on provincial export index. Similar to previous findings, effects of the BTA are increasing and persistent in the long-run. In particular, the effects accumulate from 2002 to 2008 and remain at the same magnitude until 2016. Our estimates suggest that a 1 percentage point decrease in the provincial BTA tariff leads to an average 10.79 points increase in province’s export index (column 1 of Table A3). As in section 2.5, the average provincial BTA tariff decreases by \(-10.27\) points. This suggests that the BTA has induce 110.8 percentage point increase in provincial exports to US.

We construct a similar unit-value index for each province, denoted by \(UVAL_{pt}\), and perform an analogous excercise. In this case, \(\text{log}(Export_{jt})\) in equation (2.9) is replaced by \(\text{log}(Unitvalue_{jt})\) which represents the natural log of (weighted) average unit-value of industry \(j\) in year \(t\). The results for the impact of the BTA tariff reductions on \(UVAL_{pt}\) are shown in columns (2) and (4) of Table A3. We find that the BTA has improved province-level unit-value index, even though there seems to be a strong pre-trend existing prior to 2001 for unit-value index.

To investigate whether the BTA has worked through exports overall and unit-value in

\(^{33}\)Our choice of initial year 1998 here is due to the fact that this is the first year Vietnam introduces its own MFN tariff rates, according to Import and Export Duties Law of Vietnam which is substantially amended in 1998. This choice is also consistent with our VLSS 1997/1998 data.
particular in affecting upward occupational mobility, we estimate the following model:

\[
Upward_{ipt} = \text{Index}_{pt} + X'_{ipt}\beta + \lambda_p + \lambda_t + \varepsilon_{ipt},
\]  

(2.11)

where \(\text{Index}_{pt} \in \{\text{EXI}_{pt}, \text{UVAL}_{pt}\}\). The model is first estimated with ordinary least squares (OLS). Columns (1) and (3) of Table 2.7 show the results for export and unit-value index respectively. Column (1) suggests that a one point increase in export index leads to 0.042 points increase in upward mobility. Similarly, column (3) suggests that a one point increase in unit-value index leads to 0.033 points increase in upward mobility. Notice that if we combine the result in column (1) with our results from Table A3, the estimates suggest that the BTA tariff reductions work entirely through export index i.e. 0.042 \times 10.787 = 0.45, which is almost equals to the (reduced-form) BTA effect estimates in Table 2.5. By the same token, improvements in unit-value index also appear to be driving the upward mobility. Combining the result in column (3) with our results from Table A3, the estimates suggest that the BTA tariff reductions working through upgrading provinces’ unit-value indices lead to 0.033 \times 15.652 = 0.52 point increase in upward mobility, slightly stronger than the export-index channel.

It is possible that both \(\text{EXI}_{pt}\) and \(\text{UVAL}_{pt}\) might be endogenous in equation (2.11) since provinces with higher export or unit-value index might have experienced different changes in upward mobility. To allow for this possibility, we estimate equation (2.11) with an instrumental variable (IV) approach in which we use the BTA tariff change as an instrument for either \(\text{EXI}_{pt}\) and \(\text{UVAL}_{pt}\). These results are displayed in columns (2) and (4) of Table 2.7. Our previous findings remain robust with IV estimation.\(^{34}\) Overall, we find that the BTA reductions have worked through both improving exports overall and export unit-value in particular (proxied for quality) in strengthening intergenerational occupational mobility.

\(^{34}\)The only difference incurs between columns (3) and (4), suggesting that there might be some endogeneity regarding unit-value index. Also, our IV for \(\text{UVAL}_{pt}\) is not perfect since it is possible that the BTA tariff reductions might also affect mobility through other channels such as export quantity. In that case, the exclusion restriction is violated. A more rigorous approach requires an additional instrument or properly controlling for export quantity. We leave this for future research.
This is our last key finding in this paper.

### 2.7 Conclusion

In this paper, we study the impact of a large and exogenous export shock on intergenerational mobility in Vietnam, a small and rapid-developing economy. Our results suggest that export liberalization induced by United States-Vietnam Bilateral Trade Agreement (BTA) has led to substantial increase in upward occupational mobility, accounting for one-third of overall increase in mobility in Vietnam during the past two decades. We also find that the BTA has induced more educational attainment of younger generations and worked through improving exports overall as well as unit-value in particular (proxied for quality) in promoting intergenerational mobility.

Our findings have several important implications. First and most importantly, our paper show that trade can breakdown certain frictions and social structures that impede intergenerational mobility. This leads to more equality of opportunities for younger generations, which is an important margin often missing in the trade and inequality literature. Second, if trade can promote mobility and allow high-ability individuals obtaining better jobs, this can generate additional long-term gains from trade due to more efficient allocation of resources.

There are several caveats to our current analysis, however. First even though, we were able to measure occupational mobility based on education content of each occupation, which we used as a proxy for skills, we would prefer a direct skill measure of each occupation as in Autor, Levy and Murnane (2003) and Acemoglu and Autor (2011). Second, in an attempt to separately quantify the unit-value channel of the BTA, we have used the same instrument for both variables: exports and export unit-value. Ideally, we would like an additional instrument that exogenously shifts export quantity but not unit-value. Finally, although we have access to household surveys VLSS 1992/1993 and VLSS 1997/1998, we have not been able to use them for pre-trend checks. We leave these considerations for future research.
Figure 2.1: Age and Education of Employed Workers by Gender (Top) and Urban/Rural Status (Bottom)

Note: Sample of employed workers are individuals with age between 15 and 65 who are contemporarily participating in the labor market.
Figure 2.2: (Annual) Real Wages of Employed Workers by Gender (Top) and Urban/Rural Status (Bottom) in Thousand VNDs

Note: Sample of employed workers are individuals with age between 15 and 65 who are contemporarily participating in the labor market. Annual real wages are in thousand VNDs and deflated by CPI data from the World Bank.
Figure 2.3: Persistence of Upward Occupational Mobility: Top Fathers (Top) and Bottom Fathers (Bottom)

Note: The top panel shows allocation of sons’ occupations conditioning on having top fathers (High-level Professionals). The bottom panel shows allocation of sons’ occupation conditioning on having bottom fathers (Unskilled and Agricultural Workers).
Figure 2.4: Occupational Mobility from 2002 to 2016

Note: Upward occupational mobility is fraction of sons that have better jobs than their fathers in each year. Similar definitions apply for downward and no mobility. Working sample is restricted to sons aged between 16 and 40 who are contemporarily participating in the labor market.
Figure 2.5: Vietnam’s Exports to US from 1996-2016 (in Billion US Dollars)

Note: The graph is based on authors’ calculations. The primary sectors include agriculture and mining. The data is from US Census. All values are in nominal term.
Figure 2.6: (Weighted) Average Unit Value (in US Dollars) from 1994-2018

Note: The graph shows the (weighted) average unit-value of Vietnam’s exports to US over time. Unit value is weighted by export value of each product at HS 10-digit level. The graph is based on authors' calculations. The data is from US Census. All values are in nominal term.
Figure 2.7: Vietnam’s Applied Tariffs to the Rest of the World (in %)

Note: The graph is based on authors’ calculations. The primary sectors include agriculture and mining. The data is from WITS.
Figure 2.8: The BTA Exposure across Vietnam’s Provinces and Central Cities

Note: The BTA exposure is measured as the weighted average of tariffs in which the weights are employment share of each traded industry within each province/central city from the VHLSS 2001/2002 round, following approach in Hasan, Mitra and Ural (2007), Kovak (2013). Employment share is share of workers aged between 16 and 64 recorded in the VHLSS. Traded industries include industry codes ranging from 1 to 34 using Vietnam’s industrial classification system (industry codes 40, 74, 92, 93 are excluded). The top-4 BTA exposure include Ho Chi Minh City, Da Nang, Hanoi (Ha Tay combined) and Binh Duong. The bottom-4 BTA exposure include Ca Mau, Quang Ninh, Ha Giang and Son La.
Figure 2.9: Effects of the BTA on Upward Occupational Mobility
Figure 2.10: Effects of the BTA on (Highest) Educational Attainment and Mobility
Figure 2.11: Effects of the BTA on Vietnam’s Exports to US (Province-level Regression)
Table 2.1: Number of Households and Individuals Sampled by VHLSSs across Years

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Note: Data are drawn from eight rounds of VHLSSs from 2001/2002 to 2015/2016. In 2012, the number of households available is substantially smaller than other rounds due to data restriction from Vietnam’s GSO. In each round, the recall period for the data is 12-month.
Table 2.2: Sectoral Structure (in Employment Shares) from 2002-2016

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<td>Agriculture, Sylviculture &amp; Aquaculture</td>
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<td>6.88</td>
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<td>2.98</td>
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<td>2.81</td>
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<td>0.07</td>
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<td>0.18</td>
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<td>0.15</td>
<td>+0.07</td>
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<td>0.77</td>
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<td>1.79</td>
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Note: Shares are in percentage point. Observations are weighted by the sampling weight.
Table 2.3: Occupational Structure (in Employment Shares) from 2002-2016

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<td>2.83</td>
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<td>3. Mid-level Professionals in All Fields</td>
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<td>+0.41</td>
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<td>4.80</td>
<td>5.13</td>
<td>+2.42</td>
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<td>6. Skilled Workers in Agriculture, Sylviculture, Aquaculture</td>
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<td>2.42</td>
<td>3.87</td>
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<td>7.11</td>
<td>7.12</td>
<td>6.12</td>
<td>+3.01</td>
</tr>
<tr>
<td>8. Assemblers and Machine Operators</td>
<td>2.06</td>
<td>2.29</td>
<td>2.58</td>
<td>3.06</td>
<td>4.85</td>
<td>5.69</td>
<td>5.63</td>
<td>6.69</td>
<td>+4.63</td>
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<td>9. Unskilled Workers</td>
<td>75.82</td>
<td>74.50</td>
<td>71.00</td>
<td>67.31</td>
<td>60.78</td>
<td>57.77</td>
<td>56.88</td>
<td>56.51</td>
<td>−19.31</td>
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<tr>
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<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
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<td>100.00</td>
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Note: Shares are in percentage point. Observations are weighted by the sampling weight. Two adjustment are made for VHLSS 2010-2016. First, for these survey rounds, the occupation code 63 is changed to 92 to be consistent with the definition of low-skilled workers in agriculture, sylviculture, aquaculture. Second, in occupation code 52, a large fraction of sale staffs is street-based, which is previously categorized as low-skilled. We assign sale staffs without information on wage as 95 (street-based and sales-related workers). Without these adjustments, there are abrupt jumps in shares of occupation codes 5 and 6 and a sharp decline in share of occupation code 9 from 2008-2010.
Table 2.4: Education Index ($EI$) and Ranking of Occupations

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<th>Occupation</th>
<th>Education Index</th>
<th>Ranking</th>
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<td>2. High-level Professionals in All Fields</td>
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<td>3. Mid-level Professionals in All Fields</td>
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<td>4. Elementary Professionals (Staff &amp; White-collar Personnel)</td>
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<td>3</td>
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<td>1. Leaders in All Fields and Levels</td>
<td>10.8</td>
<td>4</td>
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<tr>
<td>8. Assemblers and Machine Operators</td>
<td>9.4</td>
<td>5</td>
</tr>
<tr>
<td>5. Skilled Workers in Services</td>
<td>9.0</td>
<td>6</td>
</tr>
<tr>
<td>7. Skilled Handicraftsmen &amp; Other Skilled Manual Workers</td>
<td>8.5</td>
<td>7</td>
</tr>
<tr>
<td>9. Unskilled Workers</td>
<td>6.6</td>
<td>8</td>
</tr>
<tr>
<td>6. Skilled Workers in Agriculture, Sylviculture, Aquaculture</td>
<td>6.5</td>
<td>8</td>
</tr>
</tbody>
</table>

Note: Education indices are computed as in equation (2.1) using VHLSS 2001/2002. (9) Unskilled Workers and (6) Skilled Workers in Agriculture, Sylviculture, Aquaculture are assigned the same rank.
Table 2.5: Baseline DID Models

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<tr>
<td></td>
<td>No control</td>
<td>BTA</td>
<td>BTA and Vietnam</td>
<td>Education Controls</td>
</tr>
<tr>
<td>BTA Effects (Total)</td>
<td>-0.418* (0.249)</td>
<td>-0.474** (0.224)</td>
<td>-0.498** (0.228)</td>
<td>-0.496** (0.224)</td>
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<tr>
<td>Province VN Tariff (Applied)</td>
<td>0.195 (0.551)</td>
<td>0.195 (0.551)</td>
<td>0.195 (0.551)</td>
<td>0.195 (0.551)</td>
</tr>
<tr>
<td>Age</td>
<td>0.071*** (0.003)</td>
<td>0.071*** (0.003)</td>
<td>0.051*** (0.003)</td>
<td>0.051*** (0.003)</td>
</tr>
<tr>
<td>Age Squared</td>
<td>-0.001*** (0.000)</td>
<td>-0.001*** (0.000)</td>
<td>-0.001*** (0.000)</td>
<td>-0.001*** (0.000)</td>
</tr>
<tr>
<td>Age of Father</td>
<td>0.005*** (0.002)</td>
<td>0.005*** (0.002)</td>
<td>0.003* (0.002)</td>
<td>0.003* (0.002)</td>
</tr>
<tr>
<td>Age of Father Squared</td>
<td>-0.000** (0.000)</td>
<td>-0.000** (0.000)</td>
<td>-0.000** (0.000)</td>
<td>-0.000** (0.000)</td>
</tr>
<tr>
<td>Married</td>
<td>-0.032*** (0.005)</td>
<td>-0.032*** (0.005)</td>
<td>-0.016*** (0.004)</td>
<td>-0.016*** (0.004)</td>
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<tr>
<td>Urban</td>
<td>0.103*** (0.006)</td>
<td>0.103*** (0.006)</td>
<td>0.082*** (0.006)</td>
<td>0.082*** (0.006)</td>
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<td>Minority</td>
<td>-0.130*** (0.008)</td>
<td>-0.130*** (0.008)</td>
<td>-0.097*** (0.008)</td>
<td>-0.097*** (0.008)</td>
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<tr>
<td>Percent of Male</td>
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<td>-0.034** (0.013)</td>
<td>-0.004 (0.013)</td>
<td>-0.004 (0.013)</td>
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<td>Household Size</td>
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<td>-0.008*** (0.001)</td>
<td>-0.003*** (0.001)</td>
<td>-0.003*** (0.001)</td>
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<td>Father Skills</td>
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<td>-0.042*** (0.002)</td>
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<td>-0.052*** (0.002)</td>
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<td>0.046*** (0.004)</td>
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<td>Secondary Education</td>
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<td>0.100*** (0.005)</td>
<td>0.100*** (0.005)</td>
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<td>0.268*** (0.007)</td>
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Robust standard errors in parentheses

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Table 2.6: Extended DID Models

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Robust standard errors in parentheses
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Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Appendices

2.A  Data Appendix


There are three main issues with the VLSS 1997/1998. First, as mentioned in section 2.2, the number of households interviewed is much smaller in the VLSS as compared to VHLSSs. In 1997/1998, there are only 6000 households in the sample. Second, even though the VLSS is presumed to be representative for living standards of the population, the sampling design is different from VHLSSs. In particular, the sample is designed to be representative for the rural areas of seven geographic regions at that time (Northern Mountains, Red River Delta, North Central, Central Coast, Central Highlands, Southeast, Mekong Delta) and three categories of urban domains (Hanoi and Ho Chi Minh City, other cities, other urban areas).\footnote{In later geographic classifications, Northern Mountains is subdivided into Northwest and Northeast, making up a total of eight geographic regions.} As a result, for 24 out of 59 provinces/central cites, there is no urban household interviewed. This in turn also leads to oversampling of urban areas without using proper sampling weights. Finally, two province codes 207 (Bac Kan) and 301 (Lai Chau) are missing in the VLSS 1997/1998.\footnote{In 1996, Bac Kan (207) and Thai Nguyen (215) were created by splitting Bac Thai. It appears that code 207 in VLSS 1997/1998 is actually 215 based on VLSS 1993’s classification.}
Figure A4: Vietnam’s Exports to US from 1996-2006 (in Billion US Dollars)

Note: The graph is based on authors’ calculations. The primary sectors include agriculture and mining. The data is from US Census. All values are in nominal term.

2.B Additional Figures and Tables
### Table A3: Impact of the BTA on Exports (Province-level Regressions)

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Province Fixed Effects: Yes Yes Yes Yes  
Year Fixed Effect: Yes Yes Yes Yes  
Clustering: Yes Yes Yes Yes  

Robust standard errors in parentheses  
*** p<0.01, ** p<0.05, * p<0.1
Table A4: Allocation of Workers across 2-digit Occupations by Year

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Bibliography


Chapter 3

The Dynamic and Non-Neutral Productivity Effects of Foreign Ownership: A Nonparametric Approach

(joint work with Mary E. Lovely and Yoonseok Lee)

3.1 Introduction

The impact of foreign ownership and foreign acquisitions on domestic firms’ performance has long been a central topic in empirical studies of globalization (see for example Aitken and Harrison (1999), Javorcik (2004), Haskel, Pereira and Slaughter (2007)). Contemporary increases in foreign direct investment (FDI) and domestic manufacturing productivity, especially in China, have kept alive debate concerning causal links between these two observed phenomena.1 Although voluminous, empirical work examining the relationship has focused

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1For example, Oberfield and Raval (2014) and Lawrence (2015) identify biased technological change as a major factor in the secular decline of labor share in the US. Evidence of biased technological change is also documented by Doraszelski and Jaumandreu (2018) using panel data of Spanish manufacturing plants.
mainly on short-term and Hicks-neutral effects of foreign investment on the production processes of domestic firms. In this paper, we study two novel productivity effects of foreign ownership and foreign acquisition on domestic firms’ production function: the dynamic and the non-(Hicks)-neutral effects. The former captures the long-term gain or loss from foreign ownership, while the latter provides insight into the labor market impact of FDI-led manufacturing growth. Our empirical context is China’s high-tech manufacturing sectors from 1998-2007 and we allow for differential effects of foreign investment across investment sources.

Dynamic productivity effects of foreign ownership arise because adoption of foreign technology and management practices often takes time to fully realize. To fix ideas, consider a domestic firm that is acquired by a foreign partner with advanced technological capability. Absorption of this technology by the acquired firm requires structural transformation in both production and non-production processes. As time is needed for this adjustment, changes in measured performance may not be fully realized immediately after the acquisition, but instead accumulate gradually over a longer time horizon. Accounting for this dynamic adjustment provides a more comprehensive picture of how foreign investment affects domestic firm productivity.

Furthermore, since non-(Hicks)-neutral gains accrue from advanced production technologies deployed in developed countries, as they are often found to be capital or labor augmenting, the same technology may have similar effects in developing economies when transferred through foreign investment. Biased technological change is considered a leading cause of many structural transformations in the labor markets of developed countries (Acemoglu and Autor (2011)). If foreign investment carries advanced foreign technology content, such investment acts as a firm-level technological shock that alters the production function of recipient domestic firms, with potentially aggregate implications for the host country.

In this paper, we propose a unifying econometric framework to estimate both the dynamic

More broadly, Karabarbounis and Neiman (2013) document a global trend of declining labor share, not only in developed countries but also in developing countries.
and non-(Hicks)-neutral productivity effects of firm-level foreign investment. To achieve these goals, we first endogenize the Markov productivity process with regards to the choice of foreign ownership to recover the productivity dynamic path of firms post-foreign acquisition. Our dynamic model accounts for the time firms need to adjust to a major ownership change. Secondly, we estimate a nonparametric production function, treating foreign ownership as an input choice. This allows us to identify the non-linear effects of foreign investment on firms’ production function, permitting us to test for non-(Hicks)-neutral productivity effects. Our econometric framework uses and extends a recent nonparametric identification result for production function estimation proposed by Gandhi, Navarro and Rivers (2017) (henceforth, GNR). The GNR method is distinguished from other existing methods, such as Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015), in that its identification is grounded in economic theory rather than in functional-form assumptions, enabling us to explore the full impact on production functions due to foreign ownership.

We apply our framework to a panel dataset of Chinese high-tech manufacturing firms from 1998-2007. During this period, along with other major reforms including state enterprise restructuring and its 2001 accession to the World Trade Organization, China experienced annual inflows of over $40 billion in foreign investment, almost all in manufacturing industries.\(^2\) Contemporaneously, China’s manufacturing sectors sustained high rates of productivity growth (Brandt, Biesebroek and Zhang (2012)). This provides an ideal context to investigate the impacts of foreign investment on Chinese firms’ productivity.

Our analysis focuses on high-tech manufacturing because these are sectors where foreign partners likely have a technological advantage over Chinese domestic firms. We also further explore the differential impacts of foreign investment based on origin: investment from Organization for Economic Co-operation and Development (henceforth, OECD) member countries versus that from Hong Kong, Macau and Taiwan (henceforth, HKMT). This empirical interest is motivated by recent empirical evidence (e.g. Kamal (2015)) that HKMT

\(^2\)Value obtained from Naughton (2006), Figure 17.1. During this time period, foreign direct investment inflows averaged between 3 and 4 percent of Chinese GDP.
firms are not more productive than private domestic Chinese firms. Indeed, an unknown share of HKMT firms are actually mainland Chinese firms that establish headquarters in a neighboring locations to enjoy favorable tax treatment reserved for foreign investors (Du, Harrison and Jefferson (2012)). Our analysis supports past findings that HKMT investment has a lesser effect on productivity and we are also able to compare the dynamics of these impacts rather than the Hicks-neutral productivity term alone.

We offer three main results. First, in our baseline model, we show that foreign acquisition of a Chinese private firm improves the target firm’s productivity in both the short and long run. However, we find that the long-run effect is typically smaller than the short-run effect. Furthermore, the long-run productivity effect varies significantly across firm sizes: larger firms generally benefit from foreign ownership while smaller firms do not. Secondly, when we distinguish foreign investment coming from HKMT versus OECD-member states, we find no productivity premium relative to domestic ownership from HKMT acquisition, but a larger than average premium from OECD firm ownership. Interestingly, the production technology of HKMT-acquired firms are remarkably similar to those of private domestic firms. Finally, and importantly, we find strong evidence of non-(Hicks)-neutral impacts of OECD ownership on China’s high-tech manufacturing sectors. We find that foreign technology embedded in OECD investment has both labor- and capital-augmenting implications.

3.1.1 Foreign Ownership and Productivity Literature

The relationship between foreign ownership and firms’ productivity has been studied extensively in the literature. In most cases, researchers are interested in the short-term and Hicks-neutral productivity effects, and empirical results are mixed. For example, Djankov and Hoekman (2000), Harris (2002), Harris and Robinson (2003), Conyon et al. (2002), Girma and Gorg (2007), Arnold and Javorcik (2009), Girma et al. (2015) find that foreign-invested firms (and foreign affiliates) have higher productivity than do their domestic counterparts. In the case of foreign acquisition, foreign investment is found to boost the productivity of
domestic recipient firms. In contrast, other studies such as Griffith (1999), Benfratello and Sembenelli (2006), Fons-Rosen et al. (2013), Wang and Wang (2015) find that foreign ownership typically has no or a very small positive productivity effect post acquisitions.

This paper introduces a new econometric framework for exploring the productivity impacts of foreign acquisition, a contribution made evident by a brief review of prior empirical approaches. The most common empirical strategy in recent studies is a two-stage approach where in the first stage the researcher estimates a structural measure of firms’ performance (i.e. total factor productivity (TFP)), while in the second stage the researcher combines a difference-in-difference estimator with propensity score matching to identify an average treatment effect of foreign ownership on firms’ performance. For instance, Arnold and Javorcik (2009) employ this strategy and find that foreign investment substantially improve productivity of recipient plants in Indonesia, with an average effect of about 13.5% three years after acquisition. Wang and Wang (2015) implement this strategy to study the effect of foreign acquisition compared to domestic acquisition, finding no significant productivity advantage due to foreign equity participation. Girma and Gorg (2007) and Girma et al. (2015) apply the same strategy to UK and Chinese manufacturing, respectively, and arrive at similar qualitative conclusions. Most recently, Javorcik and Poelhekke (2017) employ this difference-in-difference approach in the context of foreign divestment in Indonesian manufacturing, finding support for the hypothesis that the benefits of foreign ownership are driven by continuous supply of headquarter services. There are two common underlying assumptions of these studies: (1) the productivity process is exogenous with regards to the choice of foreign ownership in the first-stage, and (2) the effect of foreign ownership is Hicks-neutral, meaning that it only affects the production function in a linear manner. In contrast, our econometric model relaxes these assumptions and allows the exploration of differences that are not feasible with previous empirical strategies.
3.1.2 Our Approach

Our econometric framework builds on a dynamic model of firm behavior introduced in the productivity estimation literature. This model and its structural estimation have been developed by a series of papers including Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2015) (henceforth, OP, LP and ACF, respectively) and Gandhi, Navarro and Rivers (2017). Our initial points of departure are papers by De Loecker (2013) and Doraszelski and Jaumandreu (2013), who extend productivity analysis to explore learning-by-exporting and R&D, respectively.\(^3\) Most closely related to our paper is Chen et al. (2017) who extend GNR’s nonparametric framework to study productivity dynamics of privatization in China. We follow their approach in the context of foreign investment. Both the ACF and GNR methods draw insights from OP and LP in that the levels of static inputs are determined based on firms’ current realization of productivity and hence, contain information about this unobserved characteristic. These observed static inputs can then be used to nonparametrically control for productivity. ACF combines this information with a Leontief functional-form assumption to identify the production function.

GNR extracts information from static inputs taking a somewhat different angle. In addition to using the levels of static inputs to control for productivity, GNR exploits static input shares and first order conditions to provide additional sources of information for identification. Additionally, GNR overcomes the non-parametric non-identification issue of the classic OP and LP methods and allows for more flexible extensions of the model.\(^4\)

The empirical framework we use in this paper is based on GNR, since it estimates a gross output production function and allows for flexible nonlinearities in both production technology and productivity growth. Thus, the GNR method serves our purpose by making estimation of the dynamic and non-Hicks-neutral effects feasible. Our identification is ob-

---

\(^3\)These extensions date back to Griliches (1979)’s knowledge capital model in the productivity literature.

\(^4\)See also reviews of this non-identification issue provided by Bond and Söderbom (2005), Ackerberg, Caves and Frazer (2015), Gandhi, Navarro and Rivers (2017).
tained by the firm’s first-order conditions and timing assumptions.\textsuperscript{5} In this paper, we do not distinguish between revenue productivity (TFPR) and physical productivity (TFP) as we are interested in the general performance of firms, which might include firm-specific market power as well.\textsuperscript{6}

Our approach offers several advantages. First, by endogenizing the choice of foreign ownership and allowing this choice to affect future productivity through a Markov process, we explicitly recover the productivity adjustment path of firms. This allows us to compare short-term versus long-term effects of foreign ownership and foreign acquisitions. Secondly, by estimating a nonparametric production function, we can account for the full heterogeneity of the production function. This feature is particularly important since even within a narrowly defined industry, firms with different ownership types and different scales of production may exhibit substantial heterogeneity in production technology. Finally, our framework is easily extendable to study other dimensions of ownership changes such as distinguishing between source countries of foreign investment (OCED versus HKMT).

The rest of the paper is organized as follows. In section 3.2, we describe the institutional background of foreign investment in China’s manufacturing sectors from 1998-2007. In section 3.3, we propose our empirical approach and estimation strategy. Section 3.4 details our dataset. Section 3.5 presents and discusses our results, while section 3.6 draws broader implications for our research.

### 3.2 Foreign Investment in China from 1998-2007

Table 3.1 shows aggregate shares of firm and employment by ownership type in 1998 and 2007. Two clear trends can be seen from this table. The first trend is the rapid growth in China’s private sector. In addition to robust entry of new firms, the Chinese government

\textsuperscript{5}The ACF method is more appropriate in the context where a researcher believes that the gross output production function is of Leontief form. See Ackerberg, Caves and Frazer (2015) for a more detailed discussion of their approach.

\textsuperscript{6}For a survey regarding the distinction between TFPR and TFP, see Loecker and Goldberg (2014). In this paper, we use the term “productivity” to refer to firms’ performance.
pursued a substantial program of SOE reform, the implications of which are studied by Chen et al. (2017). The second trend is a sharp increase in foreign investment in China’s manufacturing sectors during this period, with the number of HKMT-owned firms almost doubling while those with OECD investors tripling in number. The employment share of foreign-invested firms increases markedly from 6.7% to 13% for HKMT firms and from 5% to 15% for OECD firms between 1998 and 2007. Taken together, the table has two important implications. First, the number of foreign firms grows proportionally to the total number of firms in China’s manufacturing during this sample period. In addition, the scale of foreign firms is larger than that of average domestic firms. In 2007, foreign activities, measured by employment shares, account for almost 30% of Chinese manufacturing, highlighting their importance in Chinese manufacturing sector during the sample period. Therefore, at the face value, understanding the impact of foreign investment on productivity is of great importance in the China context.

The increase in economic activity of foreign firms reveals much more interesting patterns in particular sectors. Figure 3.1 captures employment share of HKMT firms and OECD firms in high-tech industries (henceforth, Tech). We define the Tech group to include industries that involve relatively more sophisticated production processes. This group of industries includes 2-digit manufacturing of: general-purpose machinery (35), special-purpose machinery (36), transportation equipments (37), electrical machinery (39), communication equipment and computers (40) and precision instruments (41). In the Tech group, the share of foreign employment increases markedly from about 7% to 16% for HKMT firms and from about 8% to 25% for OECD firms. Again, if one were to combine HKMT and OCED firms into one category, the pattern of this increase is much steeper and consequently by 2007, foreign employment accounts for about 40% of the Tech industries. Another interesting pattern captured by Figure 3.1 is that there is an abrupt surge in the employment share of OECD firms after 2003. This surge is potentially due to a major overhaul of China’s FDI policy in
2002 following China’s WTO accession that gave preferences to the high-tech sectors.\footnote{See Lu, Tao and Zhu (2017) for a review of FDI policy in China.}

### 3.3 The Model

We first start with an augmented model of a nonparametric production function. Consider the following production function:

$$y_{it} = f(k_{it}, l_{it}, m_{it}, v_{it}) + \omega_{it} + \epsilon_{it},$$  \hspace{1cm} (3.1)

where $y_{it}, k_{it}, l_{it}, m_{it}$ are the natural log of output (revenue), capital, labor, and material of firm $i$ in year $t$. $v_{it}$ is an indicator variable indicating the ownership status of the firm, whether domestic (D) or foreign (F):

$$v_{it} = \begin{cases} 
1 & \text{if Foreign (F)} \\
0 & \text{if Domestic (D)}.
\end{cases}$$  \hspace{1cm} (3.2)

$\omega_{it}$ measures productivity of the firm. As briefly mentioned before, we interpret this term as firm’s performance rather than physical productivity in order to avoid the need to identify firm markups, which is difficult in Chinese firm-level data due to the lack of firm-level price information. $\epsilon_{it}$ is a random measurement error and fully exogenous. In this model, the indicator variable $v_{it}$ captures fundamentally different technology (heterogeneity) between foreign firms (F) and domestic firms (D). We treat this $v_{it}$ as an input into the production processes of firms and allow it to be correlated with productivity $\omega_{it}$.

The second extended feature of this model is the Markov productivity process. Specifically, we consider the Markovian productivity:

$$\omega_{it} = h(\omega_{i,t-1}, d_{it}) + \eta_{it},$$  \hspace{1cm} (3.3)
where \( d_{it} \) indicates if the firm switches ownership status between domestic to foreign from period \((t-1)\) to period \(t\). If the firm indeed switches in period \(t\), this indicator variable equals 1. If otherwise (i.e. ownership status does not change), this indicator equals 0. In particular, \( d_{it} \) is defined as:

\[
d_{it} = \begin{cases} 
1 & \text{if } v_{i,t-1} = 0 \text{ and } v_{it} = 1 \\
0 & \text{otherwise} 
\end{cases}
\] (3.4)

The function \( h(.) \), which captures the expected productivity of the firm at the beginning of period \(t\), is allowed to be nonparametric.

The structures in (3.1)-(3.4) combined allow us to capture the short-run and long-run effects on productivity of firms due to foreign ownership. Here, we interpret \( v_{it} \) as capturing the permanent shift in productivity trajectory between domestic and foreign firms. On the other hand, \( d_{it} \) captures the initial difference or selection effect of firms who switch as compared to firms who do not, conditioning on the same past productivity \( \omega_{i,t-1} \). As will be clear later, if the Markov process \( h(.) \) is stationary, the initial difference or selection effect will die out over time.

Next, we follow the productivity literature in imposing the scalar unobservability assumption:

\[
m_{it} = M(k_{it}, l_{it}, v_{it}, \omega_{it}),
\] (3.5)

where \( M(.) \) is strictly monotone in \( \omega_t \), conditioning on all other inputs and state variables. Intuitively, equation (3.5) implies that more productive firms use more material inputs to produce more output, conditioning on the same market environments and on all other inputs as well as state variables such as ownership status.\(^8\) A direct result from this assumption is that function \( M(.) \) can be inverted to nonparametrically control for productivity based on

\(^8\)This assumption can be shown to hold under various market structures. See also expositions of this assumption in Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2015), Gandhi, Navarro and Rivers (2017).
observable inputs used:

\[ \omega_{it} = \mathbb{M}^{-1}(k_{it}, l_{it}, v_{it}, m_{it}). \]  

(3.6)

We also need the timing assumptions in order to identify our production function. The formal timing assumptions follow GNR and Chen et al. (2017). We describe the timing of firm’s actions as:

- At the end of period \((t - 1)\), the firm chooses \((k_{it}, l_{it}, v_{it})\) and whether to exit at \(t\).
- At the beginning of period \(t\), \(\eta_{it}\) (and hence \(\omega_{it}\)) realizes. The firm observes their productivity for period \(t\).
- The firm optimally chooses \(m_{it}\), after which \(\varepsilon_{it}\) realizes and completely determines \(y_{it}\).
- At the end of period \(t\), the firm chooses \((k_{i,t+1}, l_{i,t+1}, v_{i,t+1})\) and whether to exit at \((t + 1)\), repeating the same process.

Based on this timing structure, we have classified inputs based on their information sets. Specifically, we first assume that \(k_{it}, l_{it}\) and \(v_{it}\) are dynamic inputs that belong to the information set of the firm at the end of period \((t - 1)\), which we denote by \(\mathbb{I}_{i,t-1}\). This assumption creates exclusion restrictions between these dynamic inputs and the productivity shock \(\eta_{it}\) as well as the random measurement error \(\varepsilon_{it}\). On top of that, we also assume that \(m_{it}\) is a static input that belongs to the information set in period \(t\), which we denote by \(\mathbb{I}_{it}\), but not \(\mathbb{I}_{i,t-1}\). This means that \(m_{it}\) is allowed to be correlated with \(\eta_{it}\). However, since \(m_{it}\) is not correlated with the random measurement error \(\varepsilon_{it}\) by construction, this creates another exclusion restriction for us to identify the elasticity with respect to this input. Intuitively, capital and labor are assumed to be sticky inputs: they take time to plan, implement and go into actual production. On the other hand, firms are assumed to have full flexibility in adjusting material inputs corresponding to their temporal productivity shocks.
3.3.1 Dynamic Interpretation

It is important to clarify how we interpret the dynamics in our augmented model. Here, we follow the literature on dynamic transitions. As mentioned before, the term $v_{it}$ captures the long-run difference or heterogeneity in production technology between foreign versus domestic firms. In other words, this long-run difference can be interpreted as the long-run productivity effect for firms that switch ownership from being purely domestic to having foreign equity participation (i.e. a permanent difference between two equilibrium stages). On the other hand, the term $d_{it}$ captures the initial gap in productivity between firms who switch ownership status versus firms who do not. This gap helps us to see whether firms who switch have systematically different productivity in period $t$ as compared to firms who do not, conditioning on the same past productivity in period $(t - 1)$. In other words, this $d_{it}$ term captures any positive or negative selection associated with firms who switch their foreign ownership status.

As a result of the combined structure from (3.1)-(3.4), the immediate effect on firms switching ownership status is reflected by the total effect of $v_{it}$ and $d_{it}$. Figure 3.2 sketches out three possible dynamic transition scenarios, where switching firms experience different productivity adjustment paths with regards to immediate versus long-run effects. Depending on the sign of the initial gap captured by $d_{it}$, the immediate effect can be smaller than, equal to, or larger than the long-run effect.

In economic terms, a difference between the immediate and the long-run effects has important implications. Take, for example, the case where $d_{it}$ is positive. The positive effect of $d_{it}$ implies a positive selection of firms who switch ownership status from domestic to foreign. The contribution of this selection reduces over time and converges to a smaller long-run difference in productivity between domestic and foreign firms. The underlying intuition of this scenario is that firms who switch ownership status are expected to be more productive in period $(t+1)$ to begin with, even under the counterfactual situation where foreign acquisition does not occur. However, in the long run, this initial advantage disappears, domestic firms
catch up, and the true productivity difference between the two forms of ownership converges to a smaller level. Similar economic interpretations can be applied in the cases where \( d_{it} = 0 \) or \( d_{it} \) is negative.

Due to the nature of the nonparametric method, we are able to obtain the whole distribution of the effect after estimating the model. Nonetheless, in order to aid our interpretation, in all of our specifications, we maintain the nonparametric specification for the production function \( f(.) \) but simplify the Markov productivity process to be a linear AR(1) process, which is a widely used specification in the productivity literature. Specifically, we assume that \( h(.) \) is of the following form:

\[
\omega_{it} = \rho \omega_{i,t-1} + \gamma d_{it} + \eta_{it}.
\] (3.7)

In the Appendix, we provide analytical formulas for short- and long-run effects of interest when both the production function and the Markov process are assumed to be linear.

### 3.3.2 Non-(Hicks)-neutral Effects

We now distinguish between Hicks-neutral and non-(Hicks)-neutral effects in our econometric model. In our framework, the effect of foreign ownership is Hicks-neutral if and only if the production function in equation (3.1) can be rewritten in the following form:

\[
y_{it} = f(k_{it}, l_{it}, m_{it}) + g(v_{it}) + \omega_{it} + \varepsilon_{it}.
\] (3.8)

In econometric terms, the productivity effect of foreign ownership is Hicks-neutral if and only if production function \( f(.) \) is additively separable between the typical inputs \( k_{it}, l_{it}, m_{it} \) and the ownership indicator \( v_{it} \). An implication of the specification in equation (3.8) is that the elasticities with respect to capital, labor, material i.e. i.e. \( \frac{\partial f(.)}{\partial k}, \frac{\partial f(.)}{\partial l}, \frac{\partial f(.)}{\partial m} \) are not functions of ownership, \( v_{it} \). Importantly, since the specification in equation (3.8) is nested within our nonparametric model in equation (3.1), we can test for nonlinearities in the effects of \( v_{it} \) by
comparing our estimated elasticities under two counterfactual scenarios: when \( v_{it} = 1 \) versus when \( v_{it} = 0 \).\(^9\)

As an example, Figure 3.3 illustrates the marginal rate of technical substitution (MRTS) between labor \( (L) \) and material \( (M) \) under two counterfactual scenarios: \( v_{it} = 1 \) versus \( v_{it} = 0 \). In this figure, when a firm has foreign ownership \( (v_{it} = 1) \), MRTS is larger as compared to the case where the same firm is domestically owned, conditioning on the same amount of labor and material \( (MRTS_{LM} = \frac{\partial f}{\partial m} M_L) \). In this case, foreign ownership has labor-augmenting technology implication and effectively reduces labor share in the production function. Similar arguments and illustrations apply for the case of capital-augmenting technology.

### 3.3.3 Estimation Method

We follow closely the nonparametric estimation procedure in Gandhi, Navarro and Rivers (2017). GNR involves a two-stage procedure. In the first stage, we estimate the partial derivative of \( f(.) \) with respect to \( m_t \).\(^{10}\) In the second stage, this partial derivative is integrated up and combined with the Markov process to fully recover the production function.

The first stage of the GNR procedure makes use of the first order condition (FOC). The firm maximizes its profit with respect to material inputs conditional on the firm’s information set in period \( t \).\(^{11}\)

\[
\max_{M_t} P_t \times \mathbb{E}[F(k_t, l_t, m_t, v_t)] \times e^{(\omega t + \varepsilon_t)} | I_t] - p_t M_t. \tag{3.9}
\]

Taking FOC of this problem gives us:

\[
P_t \frac{\partial}{\partial M_t} F(k_t, l_t, m_t, v_t) e^{\omega t} \mathbb{E}[e^{\varepsilon_t}] - p_t = 0. \tag{3.10}
\]

---

\(^9\)Furthermore, we can in principle compute the labor share, capital share and material share in a counterfactual exercise where we remove all the foreign investment in China’s manufacturing in our sample period.

\(^{10}\)In this subsection, the firm index \( i \) is omitted for brevity.

\(^{11}\)An underlying assumption here is that firms take output and material prices as given conditional on \( I_t \).
Taking the log of the above equation, we get:

\[ s_t \equiv \log \frac{p_t M_t}{P_t Y_t} = \log E[e^{\varepsilon_t}] + \log \frac{\partial}{\partial m_t} f(k_t, l_t, m_t, v_t) - \varepsilon_t. \] (3.11)

We approximate the unknown partial derivative by polynomial sieves and implement a nonlinear least square (NLS) estimation procedure to separately identify the partial derivative \( \frac{\partial}{\partial m_t} f(k_t, l_t, m_t, v_t) \) (elasticity of output w.r.t material) and the random measurement error \( \varepsilon_t \) in the first stage. After identifying this slope, we integrate it up to identify the production function \( f(.) \) up to a constant \( C(.) \) as a function of \( k_t, l_t, v_t \), which is denoted by \( D^e(k_t, l_t, m_t, v_t) \). This function \( C(.) \) reflects the variation of output conditioning on the same elasticity w.r.t material and material input used.

\[ \int \frac{\partial}{\partial m_t} f(k_t, l_t, m_t, v_t) dm_t = f(k_t, l_t, m_t, v_t) + C(k_t, l_t, v_t) \equiv D^e(.) \] (3.12)

Replacing \( f(.) \) with its original form in equation (3.1), we compute the term \( \Psi_t \), defined as:

\[
\Psi_t \equiv -C(k_t, l_t, v_t) + y_t - \varepsilon_t - f(k_t, l_t, m_t, v_t) = -C(k_t, l_t, v_t) + \omega_t \] (3.13)

Now, rewriting the Markov process and making use of the exclusion restrictions described before, the following equation is nonparametrically identified:

\[
\Psi_t = - C(k_t, l_t, v_t) + h(\Psi_{t-1}, d_t) + \eta_t \]
\[
= - C(k_t, l_t, v_t) + h(\Psi_{t-1} + C(k_{t-1}, l_{t-1}, v_{t-1}), d_t) + \eta_t \] (3.14)

Since the Markov process is assumed to be a linear AR(1) process in our empirical implementations, equation (3.14) can be rewritten as:

\[
\Psi_t = - C(k_t, l_t, v_t) + \rho \Psi_{t-1} + \rho C(k_{t-1}, l_{t-1}, v_{t-1}) + \gamma d_t + \eta_t \] (3.15)
We estimate equation (3.15) with a Generalized Method of Moments (GMM) procedure, using the following moment conditions:

\[ E \left[ \eta_t \otimes \begin{pmatrix} 1 \\ \Psi_{t-1} \\ d_t \\ C_t(.) \\ C_{t-1}(.) \end{pmatrix} \right] = 0 \]  

(3.16)

This second-stage concludes our estimation implementation. One subtle point of this nonparametric model is that interpretation of the results is based on the actual parameterization using polynomial sieves. In each implementation, we approximate the nonparametric functions with second order polynomials, similar to the translog production function family. Our results are similar when we use higher-order approximations.

### 3.4 Data

Our data are drawn from the Annual Survey of Industrial Enterprises (ASIE) in China from 1998 to 2007. This is a panel survey data covering all industrial firms with sales above 5 million Renminbi (RMB). The survey encompasses more than 90% of industrial activities in China. Table A5 in the Appendix summarizes aggregate statistics of this panel dataset by year, which matches the official published data from the Chinese government and ensures the quality of our dataset. We follow Brandt, Biesebroeck and Zhang (2012) and Brandt, Biesebroeck and Zhang (2014) in basic cleaning procedures and in constructing our capital stock series using the perpetual inventory method. Foreign ownership definitions are based on the official registration types recorded in the dataset. The official threshold of foreign

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12In the actual estimation, we use more moment conditions than required to estimate our model. The extra moment conditions that makes use of information set in period \((t - 1)\) helps the model to stabilize and converges faster.
capital share to be categorized as foreign ownership is 25%. In our dataset however, 75% of foreign firms have a foreign capital share above 30%.

As previously mentioned, our empirical applications focus on the designated high-tech industries in China. Therefore, we keep only a sample of six 2-digit industries, including: general-purpose machinery (35), special-purpose machinery (36), transportation equipment (37), electrical machinery (39), communication equipment and computers (40) and precision instruments (41). Since we are mainly interested in comparing foreign firms with private domestic firms, we drop all firm-year observations that are registered as state-owned enterprises (SOE). We drop all firms that switch their ownership status more than one time in the panel. Outliers in terms of capital, labor, material and material share are also excluded from our sample. These procedures leave us with 126,397 panels spanning the 10-year period. Roughly 25% of total firm-year observations are registered as foreign firms and 75% are registered as domestic firms. During our sample period, a total of 2,017 firms switch ownership status from domestic to foreign, in which 988 firms switch to HKMT-type and 1,029 firms switch to OECD-type. Overall, the number of switchers is small relative to the whole sample size, yet it is enough to identify the dynamic effects of a change in foreign ownership status on productivity.

3.5 Results

In the baseline specification, we combine HKMT and OCED firms and treat them as having a common technology. Figure 3.4 describes the relationship between the mean predicted $\hat{f}(.)$ and particular inputs, including labor, capital and material. There are two notable patterns from Figure 3.4. First, conditioning on the same amount of labor used, foreign firms produce more output compared to domestic firms. Nevertheless, such a premium disappears when conditioning on capital and material. Our estimation thus suggests that

13Our identification exploits the profit-maximizing behavior of firms, thus it is more plausible to compare private domestic with foreign firms. Furthermore, there are very few transitions between SOE firms and foreign firms in our sample period.
technology associated with foreign ownership manifests as labor-augmenting technology \( (v_{lt}) \) primarily interacts with \( l_{lt} \). Second, from the first left panel, foreign dominance appears to be largest among firms of middle size. For some of the largest firms, such dominance is not evident, implying that large domestic firms are technologically comparable to foreign firms.

Column 1 in Table 3.2 reports our estimates of the mean elasticities with respect to each input and the parameters of the Markov process. Overall, our model delivers reasonable estimates of mean elasticities with respect to capital, labor and material. Capital over labor ratio is close to 1, reflecting the relatively capital intensive nature of the Tech industries.\(^{14}\)

We note that even though we do not impose any parametric assumption on production functions, the mean elasticity of material inputs is about 0.725, suggesting that the true production function differs from that of Leontief form.\(^{15}\)

In our baseline specification, we find that the mean predicted effect of \( v \) is zero, which we interpret as evidence against a long-term effect on productivity of changing ownership status from domestic to foreign. The coefficient for \( d \) is positive and significant, suggesting a strong positive selection of firms who switch ownership status. In particular, firms that switch ownership status have on average a 2.6% productivity premium as compared to firms who do not, subject to the same Markov process and past productivity \( \omega_{i,t-1} \). This is consistent with the previous literature, which documents the existence of positive selection for foreign acquisition. Simply put, more productive firms are more likely to be bought out by foreign investors.

The combination of \( v \) and \( d \) gives us the immediate effect of changing ownership status. The mean short-term effect is 2.6% for all domestic firms. These evaluations at mean however mask important heterogeneity of the effect. An advantage of the nonparametric method is that we can recover the entire distribution of an effect. Figure 3.5 illustrates these

\(^{14}\)We estimate our model for the textile-related industries and find a much lower ratio. For Textile (17), this ratio is 0.75. For Garments (18) and Leather (19), this ratio is about 0.5. More results regarding these sectors are available upon requests.

\(^{15}\)An implication of this result is that the use of value-added production function cannot generally be justified.
distributions, and we can see that the distribution of long-term effects is symmetric around zero. On the other hand, the distribution of immediate effects suggests that most domestic firms that get bought out will have some short-term productivity premium. Nevertheless, this premium disappears over time.

Figure 3.6 illustrates the heterogeneity of long-term and short-term effects with respect to firm size, measured by log of employment. The conditional mean function shows that for firms of smaller size \((\log(L) \leq 6)\), the long-term effect of foreign ownership is negative, implying that their production processes do not interact well with foreign technology. On the other hand, firms of larger size benefit substantially from foreign ownership. The long-term productivity premium for these firms could be as large as about 10%. One potential explanation for this heterogeneity is that larger firms often have better absorptive capacity, and hence are better equipped to take advantage of foreign technology and management practices. This result resonates the recent findings by Fons-Rosen et al. (2018). From an econometric perspective, the result implies that larger firms’ production structure more closely resembles that of foreign firms, and hence interacts better with the dummy term \(v\). Finally, for the short-run effect, our model predicts that all firms would generate some productivity gains by switching to foreign ownership, and the gain could range from 2% to 13%.

In sum, from our baseline specification, we show that the long-term effect of foreign investment is generally small and substantially heterogenous across firm sizes. We find robust evidence of a strong positive selection effect when firms switch from domestic to foreign ownership status.

### 3.5.1 HKMT versus OECD

As noted in section 3.1, some evidence suggests that HKMT firms are in fact mainland Chinese firms, yet they establish their headquarters in offshore locations to access favorable tax treatments. If this is the case, HKMT firms should not be more productive when
compared to comparable private domestic firms. We extend our baseline model to examine this hypothesis.

Specifically, the extension allows HKMT firms to behave differently as compared to OECD firms by incorporating separate dummies for these two types of firms. This extension is specified as follow:

$$y_{it} = f(k_{it}, l_{it}, m_{it}, v_{it}^{HKMT}, v_{it}^{OECD}) + \omega_{it} + \varepsilon_{it}$$  \hspace{1cm} (3.17)

with Markov productivity process:

$$\omega_{it} = \rho \omega_{i,t-1} + \gamma_1 d_{it}^{HKMT} + \gamma_2 d_{it}^{OECD} + \eta_{it}$$  \hspace{1cm} (3.18)

We report results for this extension in column 2 of Table 3.2 and in Figures 3.7-3.9. Strikingly, as illustrated in Figure 3.7, we find that HKMT firms are indeed not more productive than their domestic counterparts. In contrast, the estimated productivity premium of OECD firms as compared to domestic firms is now much larger than in the baseline model. As in the baseline case, the labor-augmenting dominance of OECD as compared to HKMT and domestic firms disappears for very large firms. Column 2 of Table 3.2 shows that HKMT firms perform worse than domestic firms, while OECD firms perform better than domestic firms in the long run. There is common positive selection among firms who switch their ownership status to either HKMT or OECD type, although the selection effect is stronger for OECD acquisitions. Firms that switch to HKMT ownership have an estimated 1.8% productivity premium and firms that switch to OECD ownership have an estimated 3.7% productivity premium compared to firms that do not switch.

We also illustrate the distribution of the short- and long-term effects, as well as their heterogeneity in Figures 3.8-3.9. Easily seen is the difference across ownership types: the distribution of HKMT effects is primarily negative, while the distribution of OECD effects is mainly positive. This reflects the generally lower estimated productivity of HKMT firms.
as compared to domestic firms.

The productivity premium of OECD firms becomes more apparent when it is disentangled from that of HKMT firms. The top two panels of Figure 3.9 show that HKMT firms are mostly not more productive than private domestic firms, and that a switch to HKMT type will not generate productivity gains. In contrast, the bottom panels of Figure 3.9 demonstrate strong patterns of both short- and long-term productivity gains for firms receiving investment from OECD sources. The long-term effect ranges from 2% to more than 5%, while the short-term effect ranges from 5% to above 10%. As before, this productivity boost matters for moderately sized firm. Even for OECD investment, the estimated foreign productivity premium disappears for firms of very large size ($\log(L)$ close to 10 in this case).

### 3.5.2 Non-(Hicks)-neutral Implications

After estimating our model, we can compute the counterfactual elasticities for each firm in our sample and examine the non-(Hicks)-neutral implications of foreign ownership. This step provides us with distributions of these elasticities with respect to labor, capital and material. Recall that if the foreign ownership productivity effect is neutral, these distributions should not be statistically different under $v = 1$ versus $v = 0$. To test for non-neutrality, Table 3.3 shows our simple paired t-test for these elasticities.

In Table 3.3, mean elasticities with respect to labor and capital are larger for foreign firms compared to domestic firms. On the other hand, the elasticity with respect to material is larger for domestic firms as compared to their foreign counterparts. These results imply that foreign technology involves more labor and capital but less material.\footnote{Furthermore, if we impose constant return to scale (CRS) assumption on the physical production function, we can infer markups induced by different ownership status. Table 3.3 shows that having foreign ownership increases firms’ markup.} Table 3.4 compares the elasticity ratios of labor and capital, taking material as a normalized input. Because for each firm, we hold the input ratios fixed, differences in these elasticity ratios essentially reflect the differences in $MRTS$, which directly maps to input factor shares. Table 3.4 shows
that MRTSs are higher for foreign firms as compared to domestic firms. Ceteris paribus, this imply that labor share and capital share of total revenue are lower in foreign firms as compared to domestic firms. Back-of-envelope calculations imply that labor would have been 1.8% higher in the absence of foreign investment in all firms in our sample.\textsuperscript{17} This evidence suggests that foreign investment is non-(Hicks)-neutral biased and may have contributed to the decline of Chinese labor share during this sample period.

Biased technological change introduced by foreign investment into China’s high-tech manufacturing may also help to explain the observed growth in the domestic value-added share of Chinese high-tech exports.\textsuperscript{18} As noted above, our estimates imply that foreign technology involves more labor and capital inputs relative to material inputs. Foreign-invested firms were an expanding presence in China’s high-tech sector over our sample period: their share of total high-tech sales rose from 27.5 percent in 1995 to 44.1% in 2005. By 2005, foreign-invested firms provided almost two-thirds of China’s total high-tech export value.\textsuperscript{19} Because foreign technology raises the contribution of domestic labor relative to imported materials, foreign investment may have contributed to the rising domestic value-added share of the sector’s exports.

### 3.6 Conclusion

In this paper, we study the dynamic and non-(Hicks)-neutral productivity effects of foreign ownership in China’s high-tech manufacturing industries from 1998-2007. In doing so, we propose an econometric framework that extends a recent nonparametric productivity estimation method developed by Gandhi, Navarro and Rivers (2017). We explicitly allow for

\textsuperscript{17} We do not make similar calculations for capital because capital might be subject to adjustment cost which we cannot take into account in our framework.

\textsuperscript{18} According to the OECD-WTO Trade in Value-Added Project, in 1995 around three-quarters of the total value of China’s information and computer technology exports reflected foreign content but by 2011 this had fallen to just over half, with similar large declines seen in other high-tech sectors, such as electrical machinery and transport equipment. See https://www.oecd.org/sti/ind/tiva/CN_2015_China.pdf.

\textsuperscript{19} Characteristics of the high-tech sector for 1995 are drawn from Huang (2003), Table 1.4, which is based on data from China’s Third Industrial Census. Comparable numbers for 2005 are calculated by the authors from the Annual Survey of Industrial Enterprises, which is described in the text.
endogenous productivity process and nonlinear effects of foreign investment. Our approach enables us to recover the productivity adjustment path of firms following foreign acquisitions (short- versus long-term effects) and to study the bias of foreign technology embedded in foreign ownership.

Overall, we find that foreign ownership does bring both short- and long-term productivity gains, although the long-term effect is generally smaller than the short-term effect. This is mostly the result of positive selection upon foreign acquisitions. We also find that these effects display substantial heterogeneity across firm sizes. Domestic medium-sized enterprises gain the most from access to foreign investment, while the largest firms see no productivity boost.

Finally, in the context of China, our empirical analysis demonstrates that HKMT firms are not more productive than their domestic counterparts and only OECD firms deliver a productivity premium. Comparing OECD-invested firms with domestic firms’ technology, we find that OECD technology is biased, meaning that it is both labor- and capital-augmenting. Thus, the foreign-investment productivity boost raises the marginal products of capital and labor relative to materials. This factor bias may offer further explanation for China’s falling labor share and for the rising domestic valued added observed in China’s high-tech exports.
Figure 3.1: Employment Share of HKMT and OECD Firms from 1998-2007 within Tech Industries

Note: The Tech group comprises 2-digit manufacturing of: general-purpose machinery (35), special-purpose machinery (36), transportation equipments (37), electrical machinery (39), communication equipments and computers (40) and precision instruments (41). Employment shares are calculated based on Chinese firm-level data.
Figure 3.2: Dynamic Transition Scenarios of Firms Switching Ownership Status

Note: The figure illustrates three dynamic transition scenarios of firms who switch ownership status from domestic to foreign (FO). \((v+d)\) captures immediate effect while \(v\) alone captures the long-run effect.
Figure 3.3: Marginal Rate of Technical Substitution ($MRTS$) under Factor Biased Counterfactuals

Note: The figure illustrates the marginal rate of technical substitution ($MRTS$) between labor ($L$) and material ($M$) under two counterfactual scenarios: $v = 1$ verus $v = 0$. 

Note: The figure illustrates the marginal rate of technical substitution ($MRTS$) between labor ($L$) and material ($M$) under two counterfactual scenarios: $v = 1$ verus $v = 0$. 
Figure 3.4: Predicted $\hat{f}(.)$ against Primary Inputs for Foreign versus Domestic Ownership in Tech Industries

Note: The figure illustrates the relationship between the mean predicted output $\hat{f}(.)$ against mean (log) primary inputs, including labor, capital and material respectively, for foreign and domestic firms. The estimation results are from the baseline model in equations (1)-(4).
Figure 3.5: Distribution of Short- and Long-term Effects for Firms Switching Ownership Status

Note: The figure illustrates the distribution of short- (left panel) and long-term (right panel) effects for firms switching ownership status from domestic \((v = 0)\) to foreign \((v = 1)\). Effects are measured in percentage point.
Figure 3.6: Mean Effects by Firm Size (in Log Employment)

Note: The figure illustrates the heterogeneity of short- (left panel) and long-term (right panel) effects based on firm size (measured in log employment). The heterogeneity is obtained a nonparametric conditional mean regression.

kernel = k奖学, degree = 0, bandwidth = 4, level = .59
Figure 3.7: Predicted $\hat{f}(.)$ against Primary Inputs for OECD, HKMT and Domestic Firms in Tech Industries

Note: The figure illustrates the relationship between the mean predicted output $\hat{f}(.)$ against mean (log) primary inputs, including labor, capital and material respectively, for OECD, HKMT and domestic firms. The estimation results are from the extended model in equations (17)-(18).
Figure 3.8: Distribution of Short- and Long-term Effects among Firms Switching Ownership Status (HKMT versus OECD)

Note: The figure illustrates the distribution of short- (left panel) and long-term (right panel) effects for firms switching ownership status from domestic to HKMT or OECD firms. Effects are measured in percentage point.
Figure 3.9: Mean Effects by Firm Size for HKMT (Top) and OECD (Bottom) Investments

Note: The figure illustrates the heterogeneity of short- (left) and long-term (right) effects based on firm size (measured in log employment). The heterogeneity is obtained a nonparametric conditional mean regression. The top panels illustrate short- and long-term effects for HKMT firms. The bottom panels illustrate short- and long-term effects for OECD firms.
Table 3.1: Firms and Employment by Ownership Category in 1998 and 2007

<table>
<thead>
<tr>
<th>Ownership</th>
<th>Number of Firms</th>
<th></th>
<th></th>
<th>Employment</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No.98 Pct98 No.07 Pct07</td>
<td>No.98 Pct98 No.07 Pct07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOE</td>
<td>39,477 33 9,463 3.6</td>
<td>27 57 11 17</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hybrid/Collective</td>
<td>42,297 35 32,414 12</td>
<td>11 24 10 16</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Private</td>
<td>18,770 16 170,888 66</td>
<td>3.3 7.1 24 39</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foreign - HKMT</td>
<td>11,480 9.5 22,164 8.5</td>
<td>3.2 6.7 8.2 13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foreign - OECD</td>
<td>8,228 6.8 25,753 9.9</td>
<td>2.3 5 9.5 15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>120,252 100 260,682 100</td>
<td>47 100 63 100</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The foreign equity threshold is 25% for both HKMT and OECD firms. Authors' calculations are based on the firm-level data.
Table 3.2: The Model Estimates for Tech Industries

<table>
<thead>
<tr>
<th>Mean Elasticities and Estimated Parameters</th>
<th>GNR1 (Baseline)</th>
<th>GNR2 (HKMT vs OECD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( k )</td>
<td>0.091</td>
<td>0.090</td>
</tr>
<tr>
<td>( l )</td>
<td>0.105</td>
<td>0.106</td>
</tr>
<tr>
<td>( m )</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>( v )</td>
<td>-0.000</td>
<td></td>
</tr>
<tr>
<td>( v^{HKMT} )</td>
<td>.</td>
<td>-0.035</td>
</tr>
<tr>
<td>( v^{OECD} )</td>
<td>.</td>
<td>0.025</td>
</tr>
<tr>
<td>( d^{all} (\gamma) )</td>
<td>0.026***</td>
<td></td>
</tr>
<tr>
<td>( (4.67) )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( d^{HKMT} (\gamma_1) )</td>
<td>.</td>
<td>0.018***</td>
</tr>
<tr>
<td>( (2.58) )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( d^{OECD} (\gamma_2) )</td>
<td>.</td>
<td>0.037***</td>
</tr>
<tr>
<td>( (5.42) )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( v + d )</td>
<td>0.026</td>
<td></td>
</tr>
<tr>
<td>( (v + d)^{HKMT} )</td>
<td>.</td>
<td>-0.017</td>
</tr>
<tr>
<td>( (v + d)^{OECD} )</td>
<td>.</td>
<td>0.063</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.895</td>
<td>0.899</td>
</tr>
</tbody>
</table>

Note: z-stats are reported in brackets. All numbers without z-stats are the means of their elasticity distributions.
Table 3.3: Paired t-test for Differences between Counterfactual Elasticities (OECD)

<table>
<thead>
<tr>
<th>Paired t-test</th>
<th>N</th>
<th>Mean ((v = 1))</th>
<th>Mean ((v = 0))</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor Elasticity</td>
<td>424610</td>
<td>0.107</td>
<td>0.104</td>
<td>0.003</td>
<td>0.000</td>
</tr>
<tr>
<td>Capital Elasticity</td>
<td>424610</td>
<td>0.102</td>
<td>0.088</td>
<td>0.013</td>
<td>0.000</td>
</tr>
<tr>
<td>Material Elasticity</td>
<td>424610</td>
<td>0.658</td>
<td>0.696</td>
<td>-0.038</td>
<td>0.000</td>
</tr>
<tr>
<td>(Revenue) Return to Scale</td>
<td></td>
<td>0.867</td>
<td>0.888</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Markup</td>
<td></td>
<td>15.34 %</td>
<td>12.61 %</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The table shows paired t-test results for elasticities under two counterfactuals: \(v = 1\) versus \(v = 0\). (Revenue) return to scale are sum of mean elasticities. Markups are inferred under the assumption of constant return to scale of physical production function.
Table 3.4: Paired t-test for Elasticity Ratios under Factor Bias Counterfactuals (OECD)

<table>
<thead>
<tr>
<th>Paired t-test</th>
<th>N</th>
<th>Mean ($v = 1$)</th>
<th>Mean ($v = 0$)</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor/Material</td>
<td>424610</td>
<td>0.172</td>
<td>0.154</td>
<td>0.018</td>
<td>0.000</td>
</tr>
<tr>
<td>Capital/Material</td>
<td>424610</td>
<td>0.162</td>
<td>0.131</td>
<td>0.031</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Note: The table shows paired t-test results for elasticity ratios under two counterfactuals: $v = 1$ versus $v = 0$. These elasticity ratios are $\frac{\partial f}{\partial l}(\cdot)$ and $\frac{\partial f}{\partial m}(\cdot)$ respectively.
3.A Dynamic Interpretation in A Linear Model

Consider the following linear (special) case of our model:

\[ y_{it} = \beta_k k_{it} + \beta_d d_{it} + \beta_m m_{it} + \beta_v v_{it} + \omega_{it} + \epsilon_{it}, \]  \hspace{1cm} (A1)

with the Markov productivity process:

\[ \omega_{it} = \rho \omega_{i,t-1} + \gamma d_{it} + \eta_{it}. \]  \hspace{1cm} (A2)

If a firm switches their ownership status in period \( t \), we would have both \( v_{it} \) and \( d_{it} \) change from 0 to 1. Therefore, the immediate gain in productivity i.e. in period \( t \) due to this switch is \( \beta_v + \gamma \). At the period \( t + 1 \), the gain would now be smaller due to stationarity of the Markov process. We specify the gains as follow:

- Period \( t \): \( \beta_v + \gamma \)
- Period \( t + 1 \): \( \beta_v + \rho \gamma \)
- Period \( t + 2 \): \( \beta_v + \rho^2 \gamma \)
- ...
- Period \( t + n \): \( \beta_v + \rho^n \gamma \)
Hence, we have the long-run effect equaled to $\beta_0$ when $n \to \infty$.

Table A5: Aggregate Summary Statistics (Monetary Values in Trillion RMB)

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Firms</th>
<th>VA</th>
<th>Sales</th>
<th>Output</th>
<th>Employment</th>
<th>Export</th>
<th>Fixed Assets (Net)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>165118</td>
<td>1.94</td>
<td>6.54</td>
<td>6.77</td>
<td>56.44</td>
<td>1.08</td>
<td>4.41</td>
</tr>
<tr>
<td>1999</td>
<td>162033</td>
<td>2.16</td>
<td>7.06</td>
<td>7.27</td>
<td>58.05</td>
<td>1.15</td>
<td>4.73</td>
</tr>
<tr>
<td>2000</td>
<td>162882</td>
<td>2.54</td>
<td>8.37</td>
<td>8.57</td>
<td>53.68</td>
<td>1.46</td>
<td>5.18</td>
</tr>
<tr>
<td>2001</td>
<td>171256</td>
<td>2.83</td>
<td>0.00</td>
<td>9.54</td>
<td>54.41</td>
<td>1.62</td>
<td>5.54</td>
</tr>
<tr>
<td>2002</td>
<td>181557</td>
<td>3.30</td>
<td>10.86</td>
<td>11.08</td>
<td>55.21</td>
<td>2.01</td>
<td>5.95</td>
</tr>
<tr>
<td>2003</td>
<td>196220</td>
<td>4.20</td>
<td>13.95</td>
<td>14.23</td>
<td>57.48</td>
<td>2.69</td>
<td>6.61</td>
</tr>
<tr>
<td>2004</td>
<td>279092</td>
<td>0.00</td>
<td>19.78</td>
<td>20.17</td>
<td>66.22</td>
<td>4.05</td>
<td>7.97</td>
</tr>
<tr>
<td>2005</td>
<td>271835</td>
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Bibliography


EDUCATION

Ph.D. in Economics, Syracuse University, 2015-2020 (Expected)
B.A. in Economics, Colorado State University, 2014 (Magna Cum Laude)
B.A. in International Business and Economics, Foreign Trade University, 2014 (Distinction)

RESEARCH FIELDS

Primary: International Trade, Labor Economics
Secondary: Applied Econometrics, Empirical IO, Development

RESEARCH EXPERIENCE

Research Assistant for Professors Devashish Mitra, Mary E. Lovely, Kristy Buzzard at Syracuse University (2017-2020)
PhD Research Intern at Asian Development Bank, Mandaluyong, Philippines (2017)

TEACHING EXPERIENCE

Instructor: Intermediate Microeconomics (Evaluation rating 4.40/5)
Teaching Assistant: Microeconomic Theory (PhD level), International Trade Theory & Policy, Intermediate Microeconomics, Intermediate Macroeconomics, Econometrics

HONORS & AWARDS

All-University Doctoral Prize in Economics, Syracuse University, 2020
Cramer Graduate Research Fellowship, Syracuse University, 2018-2020
Maxwell Dean Summer Fellowship, Syracuse University, 2015-2019