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Trade reform, oligopsony, and labor market distortion: Theory and evidence

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ABSTRACT

In a heterogeneous-firm model with oligopsonistic local labor markets, this paper shows that opening up to trade can affect distortion in such markets. The distortion arises because firms are large and able to exercise market power over their local workers. Using a panel dataset of Chinese manufacturing firms from 1998 to 2007, I measure firm-level labor market distortion and examine their evolution following China's trade policy reform in 2001. I find that labor market distortion is pervasive and the trade policy reform has led to a net reduction of the distortion in China's manufacturing sector, with a larger and significant effect working through the liberalization of input tariffs.

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, most empirical work has been based primarily on the theoretical premise that firms behave competitively in the labor market.[1] This premise stands in 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 cause distortionary effects on the economy by engaging in non-competitive conduct (see for examples Card et al. (2018), Berger et al. (2022)).[2] Since labor market

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[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 et al. (2010), Ashenfelter et al. (2010), and Dube et al. (2020).

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power is closely tied to 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 consequently 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 structure in *both* product and labor market, the latter of which is often missing in theoretical trade models. Second, from an empirical perspective, a firm's distortion in the labor market is not directly observable and, thus, requires a consistent measurement methodology. This paper offers novel approaches to both problems and provides estimates of the impact of trade policy on a firm's labor market distortion, using Chinese firm-level data and China's accession to the World Trade Organization (WTO) in 2001 as a historical policy experiment.

Formally, my analysis in this paper delivers three key contributions. I first develop a theoretical framework to formalize the notion of labor market distortion and explain how trade policy can affect firms' competitive behavior in the labor market. A new feature of the theory is that it embeds an oligopsony competition structure in the labor market into a workhorse trade model with heterogeneous firms (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 measure labor market distortion at the firm level empirically: (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 cross-validate each other, and I show that they capture patterns of oligopsony. 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 and input tariffs and the consequential changes in labor market distortion.

To preview the main theoretical results, the paper begins by deriving a reduced-form representation of labor market distortion from a firm's profit maximization problem. This reduced-form representation - the ratio between the equilibrium marginal revenue product of labor (*MRPL*) and wage (w) - summarizes all distortion in the labor market incurred by the firm, regardless of their sources. It also allows a measurement approach without imposing any structure on the labor market. The paper next develops a theoretical model to explain the mechanism through which trade policy affects distortion. To do so, I first incorporate recent microfoundations from labor economics literature to forge an oligopsony structure in the labor market, using a nested constant elasticity of substitution (CES) labor supply system as in Berger et al. (2022). This structure is then immersed in Melitz (2003)'s environment to allow for endogenous entry and exit of firms following sectoral trade shocks. In this environment, firms are assumed to be atomistic and compete monopolistically in the national product market. Yet, firms' locations are distributed over a continuum of local labor markets, within which firms are large employers. The modeling approach here is motivated by two empirical patterns observed in the data: (1) within a local labor market, there are significant entries and exits following trade liberalization, and (2) firms' local labor market share responds to trade policy.[3] The model developed provides clear and intuitive predictions for the effects of trade policy on labor market distortion. In the model, more productive firms have larger local labor market shares and exercise more market power over their workers. Starting from an initial equilibrium, when a country unilaterally opens more to trade by lowering its output tariffs, the competitive pressure from imports reduces each firm's profit. As a result, those firms at the margin, i.e., firms with productivity levels near the operating threshold, re-optimize 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 the competitive trade shock, the least productive firms exit; labor market share is reallocated towards more productive firms; thus, the average distortion increases. On the other hand, when the country lowers its input tariffs, it reduces production cost for all firms that use foreign inputs, increases each firm's profit, and induces entries of less productive firms into the market. As these firms gain market share, the average labor market distortion decreases.

Empirically, I measure firm-level labor market distortion with two approaches. The baseline approach exploits the reduced-form representation to measure the distortion nonparametrically. Specifically, I estimate the firm-level *MRPL*(s) by identifying a *revenue* production function and combine those with wage information available in production data. The production function estimation step adopts a nonparametric method recently emerged in industrial organization literature, developed by Gandhi et al. (2020) (henceforth, GNR).[4] Because this measurement approach imposes no structural assumption other than profit maximization (with respect to materials), the measure obtained here is referred to as the nonparametric measure.

The second approach to measurement exploits a unique exogenous demand shock to Chinese firms, namely the US-China Trade Policy Uncertainty (TPU) shock, to identify the labor supply elasticity facing each firm. This approach combines the insight from the pass-through and trade policy uncertainty literature, as in Amiti et al. (2019) and Handley and Limão (2017), Pierce and Schott (2016), respectively.[5] The intuition for the identification is that the TPU shock acts as an exogenous labor demand shock. Therefore, by observing the relational responses of firms in terms of wage and employment, one can trace out the elasticity of the labor supply curve facing the firms. By allowing the pattern of the response to be dependent on firms' local labor market share,

[3] Benmelech et al. (2020) document similar patterns for US manufacturing sectors. They find that employer concentration, measured by the Herfindahl-Hirschman Index, increases substantially following the import competition shock from China in the early of the 2000s. Fort et al. (2018) document that both net firm death and plant death account for the decline of US manufacturing employment and argue that both trade and technology can play a role.

[4] The GNR method is distinguished from other existing methods, such as Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), in that its identification is grounded in a firm's profit-maximizing behavior rather than in functional-form assumptions.

[5] Following 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 before its WTO accession. It is also important to note that this TPU shock of the US towards China is distinct and uncorrelated to China's own trade policy, which is the main policy focus of this paper.

this approach permits a measure of share-dependent firm-level distortion computed from regression estimates. This measure ties to the structure of the theoretical model and is thus referred to as the parametric measure.

Two main findings emerge from the empirical estimates of the labor market distortion. First, the nonparametric measure obtained from production function estimation indicates that labor market distortion is pervasive in China's manufacturing sector. The average magnitude implies a 47% pass-through rate of an idiosyncratic productivity shock to wage.[6] The parametric measure, which captures purely a firm's labor market power, on average accounts for almost 76% of the distortion obtained from nonparametric estimates. Notably, throughout my 10-year sample of Chinese firms, crucial moments of distortion distribution, such as the mean, median, and dispersion, decrease over time.

With the obtained measures in hand, I empirically assess the effects 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. The regression model compares changes in the measured distortion between firms located within the same location unit, yet are exposed differentially to trade shocks due to their industry affiliations, following the standard 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 the theoretical predictions. Qualitatively, increased import competition due to lower output tariffs leads to increased 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 to 2007 reduced labor market distortion by 3% on average. These results provide evidence that trade reform reduces overall labor market distortion in China's manufacturing sector.

Related Literature Theoretically, this 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 et al. (2022). In their paper, the CES labor supply system is micro-founded from the discrete choice model of individual workers, much like how the CES demand system is derived.[7] This paper's 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 entries and exits of firms. By modeling the product market as monopolistic competition with constant markup, 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 et al. (2012), Edmond et al. (2015) and most recently Gaubert and Itskhoki (2021). A few previous studies also integrate labor market imperfections into trade models with heterogeneous firms. Most recently, MacKenzie (2019) 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, the number of active firms in the market is assumed exogenous, and trade affects the labor market power through changes in product market power, a mechanism distinct from my model.[8] In another closely related study, Heiland and Kohler (2019) examines a theoretical model with oligopoly and oligopsony, and allows for endogenous exits due to trade. In their framework, firms are homogeneous, and oligopsony arises due to horizontal worker heterogeneity. Jha and Rodriguez-Lopez (2021) specify a trade model with monopolistic competition in the product market and monopsonistic competition in the labor market to re-examine the welfare implications of trade. Helpman et al. (2010) and Amiti and Davis (2011) also incorporate labor market imperfections into trade models. Nonetheless, 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 caused by firms' strategic behavior.

Methodologically, my paper is related to the productivity, markup, and pass-through estimation literature. Productivity estimation has recently been used to measure and study market power in the product market, for example, as in De Loecker and Warzynski (2012), Flynn et al. (2019). In trade literature, the impact of trade policy on markup has attracted considerable attention, including De Loecker (2011), De Loecker et al. (2016), Brandt et al. (2017). A growing literature has also adopted the productivity framework to study the market power of firms in factor markets, including Morlacco (2020), Brooks et al. (2021), Dobbelaere and Wiersma (2019).[9] 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 et al. (2015) (henceforth, ACF). A drawback to the ACF approach is that identifying the production function requires a Leontief functional-form assumption.[10] In this paper, I adopt the Gandhi et al. (2020)'s method (henceforth, GNR) to consistently estimate labor market distortion at the firm level. My estimation procedure does not impose functional-form assumptions.[11] To complement the production

[6] This pass-through rate would be 100% in an environment without labor market distortion.

[7] 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.

[8] At the time of writing the revision for this paper, I was also aware of ongoing work by Felix (2021) who adopts the framework in Berger et al. (2022) to investigate how trade liberalization affects labor market distortion in Brazil.

[9] Dobbelaere and Wiersma (2019) is a contemporary study that empirically investigates the impacts of trade policy on distortion in both product and labor market, exploiting the same empirical context as in this paper. The difference between this paper and their paper is theory and method. The analysis in this paper provides theory guidance and uses fundamentally different approaches to measure distortion and identify the impacts of trade policy.

[10] I estimate labor market distortion using the ACF's structural value-added approach and show that it produces unrealistically large measures of labor market distortion. See Table J2 in Appendix J and this issue encountered in Brooks et al. (2021).

[11] De Roux et al. (2021) use external instruments to estimate production functions and compare their results with existing production function estimation methods. They find that the GNR estimates come close to their estimates without external instruments. Recently, Lu et al. (2019) also adopt the GNR approach to jointly estimate a constant markup and variable wage markdowns using Chinese firm-level data. They use these measures to study the impact of foreign investment on labor market distortion using a shift-share empirical approach.

function approach, I also adopt insight from the pass-through estimation literature, as in Amiti et al. (2019), to parametrically measure the distortion. In this literature, the pass-through of international shocks to firm-level domestic prices is allowed to depend on a 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 related to a large literature on resource misallocation due to market imperfections, including Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Edmond et al. (2015), and Liu (2019), among others. In the context of China, Tombe and Zhu (2019), Cheng and Morrow (2018) also model frictions in goods and factor markets and examine their effects on productivity. However, these studies incorporate labor market frictions generically, and the frictions arise from aggregate labor supply elasticity without the layer of strategic competition. Regarding trade, my empirical results suggest that labor market distortion is large and perhaps on par with product market distortion, yet only the latter has been incorporated into the welfare calculations of trade, as in Arkolakis et al. (2012), Arkolakis et al. (2018), and others.

2. Labor market distortion and theoretical motivations

This section formalizes the notion of labor market distortion and develops a model to study the impact of a trade policy reform on firms' competitive conduct in the labor market. Section 2.1 derives a reduced-form representation of the labor market distortion. It also highlights the distinction between the distortion's exogenous and endogenous components. Section 2.2 posits the theoretical model with more structure and derives predictions.

2.1. Reduced form

Labor market distortion reflects inefficiencies in the labor market. These inefficiencies can arise from the policy/institutional environment or via the non-competitive conduct of firms. Regardless of the source, labor market distortion raises the marginal wage cost and inflicts a dead weight loss on the economy due to firms' suboptimal level of employment and production. It could also have inequality implications.

I first 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. The policy distortion is captured by a distortionary wedge χ^x and it manifests as a uniform "labor tax" imposed on the labor supply curve facing *all* firms (within the same labor market). In contrast, the labor market power distortion arises due to an upward-sloping labor supply curve $w(L_i)$ facing each firm. A classic case of this distortion is when the firm has monopsony power (Manning (2003)).

Firm's Problem Firm i maximizes its profit by solving the following problem:

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

where $R(L_i)$ is the revenue of firm i, as a function of labor L_i. $w(L_i)$ is an arbitrary labor supply function facing firm i. χ^x represents the policy distortion common to all firms. This setup does not assume that the labor market is imperfect ($w(L_i) \equiv w \quad \forall L_i$ in perfect competition), nor that workers are homogeneous across firms. In the case of a heterogeneous workforce, firms solve the same problem as in (1) if workers' average ability acts as a Hicks-neutral productivity shock (Helpman et al., 2010). For the most part of this paper, I abstract from this issue because most of China's manufacturing employment is low-skilled during my sample period.[12]

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

$$\begin{aligned} MRPL_i &= (1+\chi^x)\left(1+\underbrace{\frac{\partial w_i}{\partial L}\frac{L}{w_i}}\right)w_i \\ &= (1+\chi^x)\ \ (1+\chi_i^e)w_i, \end{aligned} \tag{2}$$

where $MRPL_i \equiv \frac{\partial R_i(.)}{\partial L}$ and w_i are, respectively, the marginal revenue product of labor and the wage paid by firm i in equilibrium. Let us further denote $\chi_i^e \equiv \frac{\partial w_i}{\partial L}\frac{L}{w_i}$ as the inverse elasticity of labor supply curve. From (2), both χ^x and χ_i^e contribute to the wedge between $MRPL_i$ and w_i. In a distortion-free economy where there is no policy distortion and the labor market is perfectly competitive, i.e., $\chi^x = 0$ and $\frac{\partial w_i}{\partial L} = 0$, $MRPL_i$ is set to equalize the wage w_i as the firm seeks to maximize profit. The roles of the exogenous distortion χ^x and the endogenous distortion χ_i^e in the firm's problem are illustrated in panels A and B of Fig. 1. Clarifying the distinction between the two types of distortion in Eq. (2) allows interpretation for the effect of trade: trade shocks shift the labor demand curve, and thus if the distortion responds to trade, the source of the response must come from the endogenous component (labor market power).

[12] In 2004, 88.4% of Chinese manufacturing workers do not have a college degree, of which 53% have only a secondary degree, and 35.4% finish high school. Source: author's calculations using Chinese firm-level data in 2004.

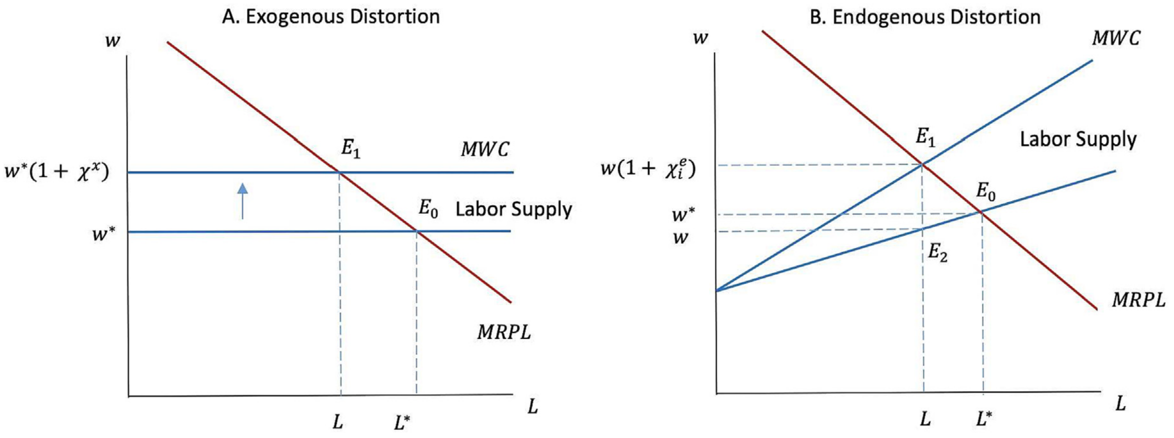

Fig. 1. Exogenous versus Endogenous Distortion in the Labor Market.
Note: The figure illustrates the exogenous versus the endogenous features of labor market distortion. Panel A (left) shows the effect of the exogenous distortion that acts as a uniform "labor tax" (χ^x) on all firms within the same local labor market. Panel B (right) shows the effect of the endogenous distortion (χ_i^e) that varies with the firm's size.

Further denote $\tilde{\chi}_i \equiv (1+\chi^x)(1+\chi_i^e)$. From (2), $\tilde{\chi}_i$ summarizes all the distortion in the labor market and has a reduced-form representation:

$$\tilde{\chi}_i = \frac{MRPL_i}{w_i}. \tag{3}$$

The expression in Eq. (3) provides straight-forward guidance to estimate 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 can be accomplished by identifying a revenue production function.[13] Although helpful in clarifying basic properties of the distortion and guiding measurement, the above setup is agnostic about which sources give rise to the endogenous labor market power distortion of firms and, thus, provides little insight into how international trade might affect firm-level distortion.

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 trade. A tradable goods sector is populated by a continuum of Home (H) and Foreign (F) firms, indexed by their productivity z, producing differentiated goods.[14] Home firms are allocated to a continuum of symmetric local labor markets indexed by n. In this model, firms are small within the goods sector but are large within a local labor market. When embedding the model to trade, 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 clear 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:

$$U = \mathbf{C} - \frac{1}{\bar{\phi}^{\phi}} \frac{\mathbf{L}^{1+\frac{1}{\phi}}}{1+\frac{1}{\phi}}, \tag{4}$$

where **C** is the sectoral consumption index that increases the household's utility, while **L** is the sectoral labor supply index that generates disutility to the household. $\phi > 0$ is the aggregate Frisch elasticity of labor supply. The household maximizes consumption subject to an exogenous budget **I** and minimizes disutility from work. The consumption index **C** is a CES aggregator of the firm-level demand $c(z)$ within the sector, similar to Melitz (2003), Atkeson and Burstein (2008), and Edmond et al. (2015):

$$\mathbf{C} = \left[\int_{\Omega^H} c^H(z)^{\frac{\gamma-1}{\gamma}} dz + \int_{\Omega^F} c^F(z)^{\frac{\gamma-1}{\gamma}} dz\right]^{\frac{\gamma}{\gamma-1}}. \tag{5}$$

[13] 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.
[14] In this section, the subscript i for the firm in the previous section is replaced by the productivity index z.

In Eq. (5), $\gamma > 1$ is the constant elasticity of substitution in demand for products across firm z. Ω^H and Ω^F are the mass of active Home firms and Foreign firms in the Home market.

The labor supply index $\mathbf{L}$ is a multi-location nested CES aggregator, a modeling technique I adopt from the recent labor economics literature (Berger et al., 2022). Specifically, the representative household allocates labor supply to each location n such that:

$$\mathbf{L} = \left[\int_{N^H} \mathbf{L}_n^{\frac{\theta+1}{\theta}} dn\right]^{\frac{\theta}{\theta+1}}. \tag{6}$$

In Eq. (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 $\mathbf{L}_n$ can be decomposed as:

$$\mathbf{L}_n = \left[\sum_{z \in Z_n} L(z)^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}}, \tag{7}$$

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 $|Z_n| = K_n$.[15] 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 et al. (2022) provide a micro-foundation for the aggregate labor supply system specified in Eqs. (6) and (7), based on a discrete choice model where each worker makes labor supply decision to each firm to maximize her/his utility.[16] 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). Underlying this nested-CES labor supply system is the existence of labor market frictions that make mobility costly for workers. In the context of China, these frictions exist because of labor market institutions such as the hukou (household registration) system. I briefly describe the hukou system in Section 3.2.

The structures in (4), (5), (6), and (7) are now sufficient to derive the product demand and labor supply facing each firm.

Product Demand From the aggregate demand system in Eq. (5), the demand function facing each firm z is:

$$c(z) = p(z)^{-\gamma}\mathbf{P}^{\gamma-1}\mathbf{I}, \tag{8}$$

where $\mathbf{P}$ and $\mathbf{I}$ are, respectively, the exogenous aggregate price index and aggregate income spent on the sector. Firm z takes the aggregate price index $\mathbf{P}$ as given in its optimization problem because it is small within the sector, whereas the aggregate expenditure $\mathbf{I}$ 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:

$$\mathbf{P} = \left[\int_{\Omega^H} p^H(z)^{1-\gamma} dz + \int_{\Omega^F} p^F(z)^{1-\gamma} dz\right]^{\frac{1}{1-\gamma}}. \tag{9}$$

Production Technology Home firms only produce and sell in the domestic market. A 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 $y(z)$:

$$y(z) = c^H(z) = zL(z), \tag{10}$$

where $L(z)$ is the labor factor use in production of firm z. 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 Eqs. (6) and (7), the labor supply function facing each firm z, located in labor market n, can be derived as:

$$L(z) = \overline{\phi} w(z)^{\eta}\mathbf{W}_n^{\theta-\eta}\mathbf{W}^{\phi-\theta}, \tag{11}$$

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

[16] The labor supply system in Berger et al. (2022) could be micro-founded from either a static or dynamic discrete choice framework for each worker. As shown in Berger et al. (2022), each worker has random preferences for working at a particular firm. The elasticity parameters η and θ govern the distribution of these 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 Eq. (5) (see also Anderson et al. (1987), Verboven (1996)).

where $\mathbf{W}_n \quad \forall n$ is a local labor market wage index, specified as:

$$\mathbf{W}_n = \left[\sum_{z \in Z_n} w(z)^{1+\eta}\right]^{\frac{1}{1+\eta}} \tag{12A}$$

and $\mathbf{W}$ is an aggregate labor supply shifter of the sector at the national level in the Home country:

$$\mathbf{W} = \left[\int_{N_H} \mathbf{W}_n^{1+\theta} dn\right]^{\frac{1}{1+\theta}}. \tag{12B}$$

Since local labor markets have measure zeros in the national economy, $\mathbf{W}$ 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 $\mathbf{W}_n$ 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:

$$\Pi(z) = p(z)c(z) - w(z)L(z) - f, \tag{13}$$

where each endogenous variable $p(z), c(z), w(z), L(z)$ is subject to the constraints given by Eqs. (8)–(11).[17] Given these constraints, the firm's problem in (13) is to decide either the optimal employment $L(z)$ or wage $w(z)$ level. Taking the FOC, I obtain the following expression for the endogenous labor market distortion of firm z:

$$\tilde{\chi}^e(z) = 1 + \chi^e(z) = \frac{MRPL(z)}{w(z)} = (1 - s(z))\left(1 + \frac{1}{\eta}\right) + s(z)\left(1 + \frac{1}{\theta}\right). \tag{14}$$

In Eq. (14), s_z is the wage-bill share of firm z within the local labor market:

$$s(z) = \frac{w(z)L(z)}{\sum_{z' \in Z_n} w(z')L(z')} = \frac{w(z)^{\eta+1}}{\sum_{z \in Z_n} w(z')^{\eta+1}}. \tag{15}$$

Eqs. (14)–(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 (η) and across-market (θ) 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 $\left(1 + \frac{1}{\eta}\right)$. 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.[18]

Entry Game and Market Equilibirum I allow for firms' endogenous entry and exit 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 turn, affect firms' local labor market share. The entry game closely follows the modeling approach for oligopoly models in international trade, such as those in Atkeson and Burstein (2008), Eaton et al. (2012), Edmond et al. (2015), and most recently Gaubert and Itskhoki (2021). The only difference in 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 Bertrand game of wage competition, i.e., firms choose the optimal wage level to maximize their profit, internalizing the effect of their own action and the action of other local firms on the local labor market.[19] Each perfectly symmetric local labor market n has access to an identical integer number of potential firms, with productivity being ranked as:

$$z^{(1)} > z^{(2)} > z^{(3)} > \ldots > z^{(k)} > \ldots \tag{16}$$

I focus on the equilibrium where firms make sequential entry decisions based on the decreasing order of their productivity ranking. In particular, the most productive firm $z^{(1)}$ makes the entry decision first, followed by the second-most productive

[17] To focus on the endogenous distortion, I have set $\chi^x = 0$ in the firm's problem in Eq. (13), as compared to the problem in Eq. (1).

[18] Recall that η is assumed to be greater to θ. Therefore, $\frac{1}{\theta} > \frac{1}{\eta}$. 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 this model in Card et al. (2018), Jha and Rodriguez-Lopez (2021)).

[19] I use Bertrand competition in this model as it is more natural to my subsequent proofs. However, in this environment, it can be shown that Cournot competition provides an identical outcome for the model, as being used in Berger et al. (2022) without entry.

firm $z^{(2)}$, and so on. When making entry decisions, each firm can perfectly compute 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:

$$\Pi^K\left(z^{(k)}\right) \geq 0. \tag{17}$$

Notice that in Eq. (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 model's equilibrium, its existence, and its uniqueness.

Proposition 1. *An equilibrium in the environment set up by Eqs. (5)–(11), 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 Theory Appendix A.

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:

$$\Pi^K\left(z^{(k)}\right) \geq \Pi^{K+1}\left(z^{(k)}\right) \geq \Pi^{K+1}\left(z^{(k+1)}\right). \tag{18}$$

Intuitively, Eq. (18) states that more productive firms always have higher profits than less productive firms given any market conditions (the latter inequality). Not only so, more productive firms earn higher profits 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 (τ^O) and the input tariff (τ^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 implication of the input tariff when the production function involves an intermediate input, which requires a slight modification of the production function in Eq. (10).

Trade shocks working through changes in the output tariff (τ^O) transmit their competitive pressure to the aggregate price index, i.e., $\mathbf{P}(\tau^O)$. This price index, in turn, shifts firms' labor demand and consequently affects the local labor market equilibrium. To see this, in Eq. (9), I assume that the mass of Foreign firms selling in the Home market Ω^F is subject to an ad-valorem tariff τ^O such that the price received by the Foreign firms, denoted by $p^{F*}(z)$, is a fraction of the Home market price $p^F(z)$:

$$p^F(z) = \left(1+\tau^O\right)p^{F*}(z). \tag{19}$$

To simplify the model, I also assume that the Home country is a small open economy. This assumption has two implications. First, Ω^F can be held fixed, and $p^{F*}(z)$ does not respond to changes in the Home market environment. Second, when there are entries and exits of firms in the Home market in response to tariff changes, this assumption guarantees a monotonic movement in the aggregate price as a function of tariff.[21] It is straightforward to rewrite Eq. (9) in the following form and show that the aggregate price index $\mathbf{P}$ is an increasing function of the output tariffs τ^O:

$$\mathbf{P}\left(\tau^O\right) = \left[\int_{\Omega^H} p^H(z)^{1-\gamma}dz + \left(1+\tau^O\right)^{1-\gamma}\int_{\Omega^F} p^{F*}(z)^{1-\gamma}dz\right]^{\frac{1}{1-\gamma}}, \tag{20}$$

[20] As in oligopoly-type models, there are multiple equilibria in this environment if the entry game is specified differently. However, these equilibria are often intractable and uninteresting. By requiring firms to make sequential moves in a particular order, I can turn attention to a most informative equilibrium. Edmond et al. (2015) shows in their quantitative exercise that the exact ordering of moves matters little in practice. The term *profit monotonicity* is coined by Eaton et al. (2012) when describing the equilibrium in their oligopoly model.

[21] For empirical context, China's economy is still relatively small compared to the world's GDP during my sample period 1998–2007. In particular, this share increases from 2.7% in 1998 to 5.05% in 2007. Source: https://www.theglobaleconomy.com/china/gdp_share/.

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

$$MRPL(z) = z^{\frac{\gamma-1}{\gamma}} L(z)^{-\frac{1}{\gamma}} \mathbf{P}\left(\tau^O\right)^{\frac{\gamma-1}{\gamma}} \Xi, \tag{21}$$

where $\Xi = \left(\frac{\gamma-1}{\gamma}\right)\mathbf{I}^{\frac{1}{\gamma}} > 0$ is an aggregate constant. As can be seen from Eqs. (20)–(21), tariff changes affect the aggregate price index $\mathbf{P}(\tau^O)$ and shift the $MRPL(z)$ curve. Firms observe these changes in the aggregate environment, re-calculate their profit considering the labor market's competition structure, and decide if they should operate, and if operating, the optimal wage level. From proposition 1 and starting from an equilibrium with a high-level output tariff, there exists a "cut-off" firm that represents the least productive 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.[22] 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 Eqs. (5)–(11), in which firms make sequential entry decisions based on the decreasing order of their productivity ranking,* ***lowering*** *output tariffs (τ^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^* is weakly increasing in (τ^O), and for $\forall z \geq z^{(K^*)}$, $s'(\tau^O,.) \leq 0$, $\tilde{\chi}e'(\tau^O,.) \leq 0$.*

Proof. See the Theory Appendix A.

To consider the effect of an input tariff change, I need to modify the production function in Eq. (10) to involve an intermediate input. Specifically, the modified production function is as follows:

$$y(z) = c^H(z) = zL(z)^{\alpha} M(z)^{1-\alpha}, \tag{22}$$

where $M(z)$ is the intermediate input used by firm z, and α 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, and subject to the Home country's input tariff (τ^I). More formally:

$$p_M = p_M^{World}\left(1+\tau^I\right). \tag{23}$$

From the Eqs. (22)–(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, $z^{(K^*+1)}, z^{(K^*+2)}, \ldots$ Furthermore, the magnitude of the effect by the input tariff is magnified by a factor of $\frac{(1-\alpha)(\frac{\gamma-1}{\gamma})}{1-(1-\alpha)(\frac{\gamma-1}{\gamma})}$, which is the adjusted relative factor share between labor and intermediate input.[23] The impact of the input tariff on market equilibrium is summarized by proposition 3.[24]

Proposition 3. ***(Equilibrium with Input Tariff)*** *Under the environment set up by Eqs. (5)–(11) and with modifications in Eqs. (22)–(23), in which firms make sequential entry decisions based on the decreasing order of their productivity ranking,* ***lowering*** *input tariffs (τ^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^* is weakly decreasing in (τ^I), and for $\forall z \geq z^{(K^*)}$, $s'(\tau^I,.) \geq 0$, $\tilde{\chi}e'(\tau^I,.) \geq 0$. Furthermore, compared to the output tariff, the impact of the input tariff on labor demand is magnified by $\frac{(1-\alpha)(\frac{\gamma-1}{\gamma})}{1-(1-\alpha)(\frac{\gamma-1}{\gamma})}$, the adjusted relative factor share between labor and intermediate input.*

Proof. See the Theory Appendix A.

[22] This mechanism is similar to the canonical Melitz (2003) model. However, no labor market distortion exists in Melitz (2003). Jha and Rodriguez-Lopez (2021) 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.

[23] This adjusted relative factor share converges to $\frac{1-\alpha}{\alpha}$ as $\gamma \to \infty$ i.e. the case of perfect competition in product market.

[24] The production function in Eq. (22) assumes unit elasticity of substitution and constant relative factor share between labor and intermediate input. Relaxing this assumption using a CES form, e.g. $y(z) = z\left[\alpha L(z)^{\rho} + (1-\alpha)M(z)^{\rho}\right]^{\frac{1}{\rho}}$, has a number of interesting implications. First, the effect of input tariffs on labor demand is heterogeneous across firms, depending on the initial use of intermediate input relative to other factors. Second, because relative factor share is now endogenous to factor prices, the effect of input tariffs is also heterogeneous over time (if trade liberalization is gradual). Previous work by Goldberg et al. (2010), Boehm et al. (2022), Ding (2020) have emphasized the role of intermediate input in shaping a firm's production. In this case, the model's main prediction still holds by imposing a correlation between productivity and input use, and some derivations are available upon request.

Proposition 3 concludes my theoretical analysis. Before moving on to the empirical analysis, it is important to note that all the predictions in propositions 1–3 are partial equilibrium results. They still hold if the product market is assumed to be perfectly competitive.[25]

3. Measuring labor market distortion (nonparametric measure)

This section develops a production-based framework to measure the (overall) distortion at the firm level. Because this approach imposes no functional-form assumption on product demand, labor supply, and production function, I refer to the measure obtained here as the nonparametric measure.

3.1. Measuring distortion from production data

My strategy to measure labor market distortion follows directly from Eq. (3). To simplify notation, I omit the subscript i when it does not cause confusion. It is convenient to rewrite the expression of the distortion in Eq. (3) as follows:

$$\tilde{\chi} \equiv \frac{MRPL}{w} = \frac{\frac{\partial R(.)}{\partial L}}{w} = \frac{\frac{\partial r(.)}{\partial l}\frac{R}{L}}{w} = \frac{\frac{\partial r(.)}{\partial l}}{\frac{wL}{R}}, \tag{24}$$

where r and l, respectively, are the natural logs of revenue and labor factor. Denoting the labor elasticity of revenue as $\theta^L \equiv \frac{\partial r(.)}{\partial l}$, and the wage-bill share of revenue as $\alpha^L \equiv \frac{wL}{R}$, the distortion $\tilde{\chi}$ in Eq. (24) could now be expressed as[26]:

$$\tilde{\chi} = \frac{\theta^L}{\alpha^L}. \tag{25}$$

Since information about the wage bill is readily available in most production datasets, the task now is to estimate the labor elasticity of revenue $\left(\theta^L\right)$. I begin by specifying a *revenue* production function of a firm in the log-form as follows:

$$r_t = f(k_t, l_t, m_t) + \omega_t + \varepsilon_t, \tag{26}$$

where r_t, k_t, l_t, m_t are the natural logs of revenue, capital, labor, and material. ω_t measures the revenue productivity, i.e., revenue TFP, in period t, and ε_t is a random measurement error. Here, $f(.)$ is a revenue production function and is allowed to be nonparametric. I also assume that $f(.)$ is differentiable at all $(k_t, l_t, m_t) \in \mathbb{R}^3_{++}$.[27,28]

Identification and Estimation of Production Function I build on a recent nonparametric estimation method developed by Gandhi et al. (2020) (hereafter, the GNR method) to estimate production function (26). 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 contrast to other existing methods such as those proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), GNR exploits an additional moment of the data derived from profit-maximizing behavior of the firm with respect to materials to identify this input's elasticity of revenue. In what follows, I briefly describe how I adapt the GNR method to consistently estimate the labor elasticity of revenue, θ^L. A distinct feature of my approach as compared to the original GNR's exposition is that I do not need to assume perfect competition (or any type of market structure) in the product market since my goal is to identify a revenue production function.[29]

My estimation procedure is implemented in two stages. In the first stage, the firm's profit-maximizing behavior to the material is exploited to provide identification information for the revenue elasticity of material, i.e., $\frac{\partial r(.)}{\partial m}$. The intuition is that when firms maximize profit with respect to factor inputs, revenue elasticities have to be equal to expenditure shares for all factors that are *not* subject to market frictions. In this case, I assume that the material market is relatively frictionless, and hence, material

[25] In fact, perfect competition in the product market is a special case of this model.

[26] Notice that the wage-bill share of revenue here (α^L) is the expenditure share on labor within each firm, and different from the local labor market wage-bill share defined in Section 2.

[27] The specification of the (log) revenue production function in Eq. (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.

[28] In addition, the specification in Eq. (26) implicitly assumes that productivity shock to each firm is Hicks-neutral. There is evidence that productivity growth can have non-neutral implications (Doraszelski and Jaumandreu (2018), Zhang (2019), Raval (2019), Lee et al. (2021)). I abstract from this issue since the identification of production function, in that case, requires either a different set of assumptions, an explicit technological shock, or better data.

[29] This is an important advantage in estimating labor market distortion as compared to the problem of estimating product market distortion (markup). In the former problem, one can sidestep the issue of identifying a physical production function, which is challenging without firm-level price information or in the presence of multi-product firms.

expenditure share is informative about this factor's elasticity of revenue.[30] Following GNR, in the first stage, I estimate the following share-regression using a nonlinear least-square (NLS) procedure[31]:

$$log\left(s_t^M\right) = log\frac{\partial}{\partial m_t}f(k_t, l_t, m_t) - \varepsilon_t. \tag{27}$$

In Eq. (27), s_t^M is the expenditure share of material obtained directly from the data and is defined as $s_t^M = \frac{p_t^M M_t}{R_t}$. The nonparametric elasticity function $\frac{\partial f(.)}{\partial m_t}$ is approximated by a second-order polynomial sieve. The estimation of Eq. (27) provides me with two outputs to use in the second stage: the revenue elasticity of material $\frac{\partial \hat{f}(.)}{\partial m_t}$, and the random shock $\hat{\varepsilon}_t$.

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

$$\int \frac{\partial}{\partial m_t}f(k_t, l_t, m_t)dm_t = f(k_t, l_t, m_t) + C(k_t, l_t) \equiv D^\varepsilon(k_t, l_t, m_t). \tag{28}$$

Plug the expression in Eq. (28) back to the original specification of production function in Eq. (26), I can rewrite the productivity term as:

$$\omega_t = \left(r_t - \varepsilon_t - D^\varepsilon(.)\right) + C(k_t, l_t). \tag{29}$$

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

$$\omega_t = h(\omega_{t-1}) + \eta_t, \tag{30}$$

where η_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 η_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 η_t is the material m_t, the elasticity with respect to which is already identified in the first stage. The Markov productivity process in Eq. (30) provides exclusion restrictions needed to identify the function $C(.)$. Let's denote $\Psi_t \equiv r_t - \varepsilon_t - D^\varepsilon(.)$, and combine Eqs. (29)–(30), I can now rewrite the Markov productivity process as:

$$\Psi_t = -C(k_t, l_t) + h(\Psi_{t-1} + C(k_{t-1}, l_{t-1})) + \eta_t. \tag{31}$$

Eq. (31) nonparametrically identifies $C(.)$ and $h(.)$, and in turn, provides identification of the revenue production function. Estimation of Eq. (31) is performed using a GMM procedure.[32] In my estimation, other than primary factors such as capital and labor, I also control for a vector of state variables that may affect the input demand decision of firms, including year, location and industry fixed effects, firm's ownership type (state-owned and foreign-owned), export status, output and input tariff levels associated with the firm's industry.

Here, it is also a good opportunity to highlight some practical issues regarding the measurement of main variables used in production function estimation. Even though capital, labor, and material in Eq. (26) are stated in terms of quantity, in practice, only labor can be truthfully measured in quantity. This gives rise to the possibility of potential input price biases for production function estimation as noted in De Loecker and Goldberg (2014). In the empirical context of Chinese firm-level data, for capital input, I use the real capital stock measure developed by Brandt et al. (2012). For material input, I use the industry input deflators developed by Brandt et al. (2017) to obtain a proxy for material quantity. These attempts, however, cannot eliminate all potential biases arising from within-industry input price variations. The production function estimation can be affected if input price variations across firms are correlated with productivity.[33] To this end, I assume that input prices (whether for capital or material) are monotonic functions of productivity, and thus, the deflated material can still be used to nonparametrically control for any

[30] In 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 a firm does 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 et al. (2015). So far, I am not aware of any empirical work that documents systematic market power in the market for material in China, except for Rubens (2021) for the tobacco industry. All my subsequent results are robust to excluding the tobacco industry in the analyses.

[31] The (modified) derivation of this share-regression from the firm's FOC is provided in Appendix B.

[32] See details of this GMM procedure in Appendix B.

[33] The GNR method helps to alleviate the concern that the price variation in material affects the estimated revenue elasticity for material because this information is obtained from the material share of revenue (see this point in the example on page 10 of De Loecker and Goldberg (2014)). However, such variation could still affect the estimated elasticities for capital and labor.

potential correlation between input use and unobserved productivity of firms. This is a general drawback of production function estimation in many contexts that one should keep in mind.

Compute the Distortion Given estimates from the revenue production function, I can now compute the empirical measure of the labor market distortion expressed in Eq. (25). Since ε_t is a random measurement error and does not affect a firm's labor demand decision, I need to correct for this term in calculating the *expected* revenue that enters the denominator of the distortion in Eqs. (24)–(25). The estimation of Eq. (27) in the first stage does provide me with an estimate of the measurement error, i.e., $\hat{\varepsilon}_t$. The measure of the distortion, therefore, can be computed as:

$$\tilde{\chi} = \frac{\hat{\theta}^L}{\hat{\alpha}^L} = \frac{\frac{\partial \hat{r}(.)}{\partial l}}{\frac{wL}{R} \times \exp(\hat{\varepsilon}_t)}. \tag{32}$$

This final step concludes the procedure to nonparametrically measure the distortion based on production function estimation.[34] Before moving on, it is important to note that the identification of labor elasticity in the GNR method does not contradict the presence of labor market imperfections. The reason is that its identification does not use the optimizing behavior of firms with respect to labor to identify the labor elasticity. In fact, it is the intuition that by combining information from industry production technology (which is informative about labor elasticity) with wages (which reveals firms' behavior in the labor market), it is possible to come up with a measure of labor market distortion.[35,36]

3.2. China's firm-level data & labor market institutions

Firm-level Data The firm-level data come from China's Annual Survey of Industrial Enterprises (ASIE) from 1998 to 2007. This dataset is a rather standard panel dataset covering all private industrial 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 et al. (2014)). Table J1 in Appendix J reports the main aggregate statistics of this dataset, which matches with published official statistics from 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, and 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 final cleaned sample consists of 1,235,801 firm-year observations, spanning over 10 years, and 422 four-digit industries. The dataset requires a thorough filtering process, which I elaborate on in Appendix C.

Labor Market Institutions My theory and empirics rely on the assumption that labor market frictions exist such that they prevent perfect labor mobility between locations (and industries), which in turn gives rise to a firm's oligopsony power. During my sample period in China, labor market frictions are still substantial. These frictions and the resulting high migration cost for workers are documented in Tombe and Zhu (2019) and Fan (2019). One of the main driving factors of such high cost is the *hukou* (household registration) system. The hukou system (dates back to 1958) is a central planning tool the Chinese government uses to control population mobility. Under this system, each person is tied to her/his hukou registration location and cannot move without permission. The system's main purpose is to control rural-urban migration flows. Nonetheless, it has strong ramifications for mobility both within and between locations.[37] Although gradual reforms eased mobility restrictions over time, the migration cost remains high (see Tombe and Zhu (2019)). Meng (2012) argues that, during the similar period up until at least 2005, *"inherited institutional impediments [including hukou system] still play an important role in the allocation of labor"*. It is the existence of these underlying impediments that gives rise to the labor market power of firms and permits trade to have impacts on such distortion. In my subsequent analyses where it matters, I control for location-year fixed effects to partial out these changes in the supply side of the labor market and focus on demand-side effects of trade policy, which works through a firm's industry attachment.

Throughout the paper, I use prefecture as the location unit.[38] This is a relevant administrative unit that has the authority to set labor market regulations such as the hukou registration and the minimum wage policy and has also been discussed and used elsewhere, for example, as in Bai et al. (2018), Fan (2019). The final firm-level dataset covers 461 prefectures over its sample period. The local labor market is constituted by 4-digit industry(j) $\times$ prefecture(l) cell.

[34] Formulas in Eqs. (24) and (32) might appear similar to those in markup estimation literature, for example in Loecker and Unger (2020). However, an important distinction is that θ^L here denotes the labor elasticity of revenue rather than the labor elasticity of physical output as in markup literature. Firm-level markup can be computed as the ratio between output and revenue elasticity.

[35] There are other studies that estimate production function using Chinese firm-level data to measure labor market distortion. Most relatedly, Brooks et al. (2021) estimate a production function using ACF's semiparametric method to measure both markup and wage markdown. My approach is different in that it does not require markup estimates, and its identification does not rely on functional-form assumption. In another related study, Lu et al. (2019) adopt the GNR method, which is very similar to my approach. However, they assume that markup is constant across firms within the same industry.

[36] In the regression analysis in Section 5, I check the robustness of my main empirical results with an alternative measure that also exploits the intuition from the production function approach here (used in Bau and Matray (2020)). However, this alternative measure assumes that the production function is Cobb-Douglas within each industry and thus does not require production function estimation.

[37] See more discussions and statistics in Chan (2010), Meng (2012), Tombe and Zhu (2019) among others.

[38] This location unit corresponds to the 4-digit geographic code in the Chinese firm-level dataset.

Table 1
Revenue Elasticities and Labor Market Distortion by Industry.

Industry (2-digit)	Capital	Labor	Material	RTS	$\tilde{\chi}_i$		No. Obs
					Mean	**Median**	
13. Food Processing	0.06	0.08	0.74	0.88	3.78	3.05	82,053
14. Food Production	0.07	0.08	0.72	0.88	2.05	1.44	27,364
15. Beverage	0.09	0.09	0.69	0.87	2.64	2.01	19,320
16. Tobacco	0.15	0.09	0.68	0.92	2.71	1.61	292
17. Textile	0.06	0.09	0.76	0.91	1.92	1.51	121,957
18. Garments	0.05	0.13	0.74	0.92	1.68	1.26	60,693
19. Leather	0.05	0.12	0.75	0.92	1.95	1.33	30,324
20. Timber	0.07	0.10	0.73	0.90	2.38	1.85	26,262
21. Furniture	0.05	0.12	0.74	0.91	2.26	1.64	15,095
22. Paper-making	0.07	0.09	0.75	0.91	2.34	1.89	43,527
23. Printing	0.10	0.08	0.72	0.90	1.42	1.07	19,681
24. Cultural	0.06	0.11	0.74	0.91	1.55	1.16	16,607
25. Petroleum Processing	0.09	0.09	0.73	0.91	4.10	3.12	9043
26. Raw Chemical	0.07	0.07	0.74	0.88	2.42	1.74	96,313
27. Medical	0.10	0.11	0.67	0.89	2.81	2.04	27,294
28. Chemical Fibre	0.07	0.08	0.78	0.94	2.70	2.12	4846
29. Rubber	0.07	0.08	0.73	0.88	1.72	1.19	14,627
30. Plastic	0.07	0.09	0.75	0.91	1.98	1.48	57,820
31. Nonmetal Products	0.08	0.08	0.71	0.87	1.39	1.03	119,861
32. Processing of Ferrous	0.08	0.11	0.75	0.94	4.38	3.61	27,350
33. Processing of Nonferrous	0.07	0.09	0.76	0.91	3.59	2.78	17,732
34. Metal Products	0.07	0.08	0.75	0.89	1.66	1.22	61,938
35. Ordinary Machinery	0.08	0.08	0.73	0.89	1.71	1.25	92,698
36. Special Equipment	0.07	0.09	0.71	0.88	1.92	1.33	44,498
37. Transport Equipment	0.08	0.10	0.73	0.91	1.98	1.44	55,002
39. Electric Machinery	0.08	0.08	0.75	0.91	2.08	1.44	73,071
40. Electronic and Telecom	0.08	0.11	0.72	0.91	1.94	1.40	34,765
41. Measuring Instruments	0.07	0.10	0.71	0.88	1.61	1.20	15,188
42. Art Work	0.05	0.10	0.73	0.88	1.53	1.09	20,580
All Industry	0.07	0.09	0.74	0.90	2.14	1.49	1,235,801

Note: The table reports estimated statistics of the revenue elasticities of factors (capital, labor, material), the revenue return to scale (RTS), and the measured distortion ($\tilde{\chi}_i$) from production function estimation in Section 3. All statistics are the mean of respective distributions, except for the distortion, where both the mean and median are reported. The table trims observations above and below the 0.5^{th} and 99.5^{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 markup. If the constant RTS of the physical production function assumption is imposed, the average markup of the Chinese manufacturing sector is 11%.

3.3. Empirical measure of distortion

Table 1 reports the empirical results for the revenue elasticities 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 0.09, and an average material elasticity of 0.74. The average revenue return to scale (RTS), is 0.90.[39] The average magnitude of the labor market distortion $\tilde{\chi}$ estimated for China's whole manufacturing sector is 2.14, implying an average *overall* pass-through rate of 47% of an idiosyncratic demand shock to wage. This pass-through rate suggests that, for instance, of a productivity shock that increases the marginal revenue product of a worker by one dollar, only 47 cents is shared with the worker in the form of wage payment. The median value of the estimated distortion is 1.49, indicating that the distribution of the firm-level distortion is skewed to the right. Across all industries, the distortion's mean and median 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 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. The left panel of Fig. 2 illustrates the distribution of $log\ (\tilde{\chi}_i)$ for the whole sample. As one can see, the log of this distribution is well on the right of the zero (no distortion) threshold. The right panel of Fig. 2 displays the evolution of labor market distortion distribution over three equidistant years within my sample period: 1999, 2003, and 2007. Across the three years, the distribution of distortion has shifted to the left, with decreases in both the mean and median. Furthermore, the dispersion of distortion distribution has also reduced substantially.[40]

[39] If one is willing to impose constant RTS of *physical* production to the whole Chinese manufacturing sector, this revenue RTS implies the average markup of 1.11 (or 11%) for the sector. This approach has been developed by Flynn et al. (2019) to estimate the markup for the US. In Section 5, I adopt this approach to measure markup for Chinese firms.

[40] 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 Linhui (2015), Morlacco (2020), Bau and Matray (2020).

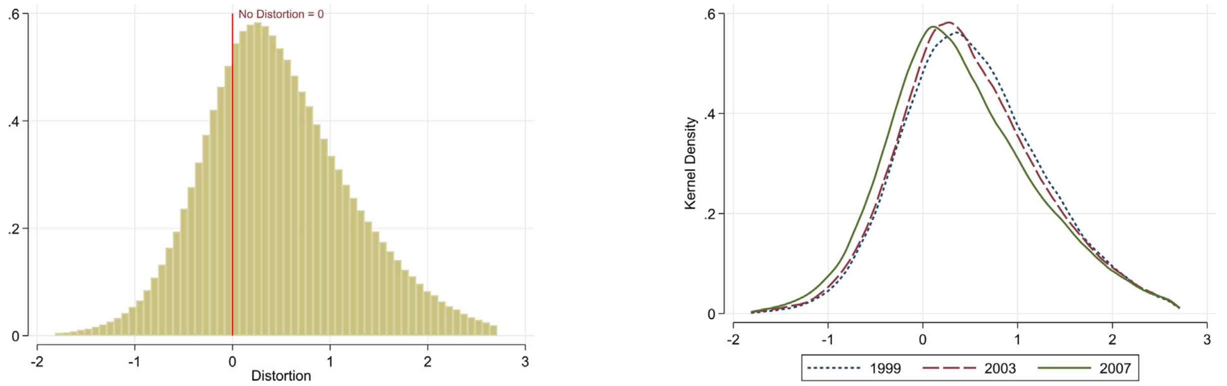

Fig. 2. Distribution of the Labor Market Distortion ($log\ (\tilde{\chi}_i)$).
Note: The figure illustrates the histogram (left) and kernel density (right) of the log-measured labor market distortion ($\tilde{\chi}_i$) from production function estimation. The left panel shows the distribution of distortion across all firm-year observations. No distortion cutoff is where $log\ (\tilde{\chi}_i) = 0$. The right panel displays the evolution of distortion distribution over three equidistant years: 1999, 2003, and 2007.

Labor Market Distortion across Industries The theory in Section 2 is limited in its ability to explain heterogeneity patterns of distortion based on observable characteristics other than productivity. Empirically, however, the distortion is likely co-determined by many factors, and it might be interesting to examine the correlation of the distortion along several heterogeneity dimensions (where possible). These correlations can be useful to motivate further analysis and future study.

In Fig. 3, I show the patterns of correlation between the distortion and several observed two-digit industry characteristics which might potentially be associated with the degree of labor market distortion, including industry's export share, state ownership (employment) share, high-skill employment ratio, and female employment share.[41] The data for industry-level characteristics are extracted from the firm-level data for 2004 when more detailed information is reported for each firm.[42] The top panels of Fig. 3 illustrate that more export-oriented industries tend to have lower levels of labor market distortion. In comparison, industries with higher shares of state ownership exhibit higher distortion levels. This pattern suggests that firms in exporting industries might compete more fiercely for labor while firms in SOE-dominated industries potentially see a lesser degree of competition, perhaps due to the presence of SOE firms.[43] 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 ratios. Indeed, firms in industries with a relatively high share of female workers, such as textile (17), garments (18), and leather (19), typically have lower distortion. On the other hand, firms in industries employing relatively more skilled workers, such as medical equipment (27), chemical fibre (28), processing of ferrous (32), and nonferrous metal (33), have higher distortion. These latter correlations are harder to interpret based on current theory and would require further study on how female or skilled labor supply interacts with industry production.

There is no particular reason why one should only look at the correlation of the distortion with the few observed industry characteristics above, and further analysis is possible. Within the extent of this paper, the correlations presented here motivate some heterogeneous analyses of the effect of trade policy across industries that I explore in Section 5.[44]

Labor Market Distortion across Firms To examine the correlation patterns of distortion across firms, I correlate firm-level labor market distortion with measured productivity, employment size, export status, ownership status, local labor market concentration, and local minimum wage. As shown in Table 2, more productive firms have higher levels 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.[45]

Linking Distortion Measurement to Oligopsony Importantly, local labor market characteristics are significantly associated with firm-level labor market distortion. Column (5) shows that more concentrated labor markets are associated with higher firm-level distortion. Similarly, firms in areas with higher relative minimum wages also incur less distortion. To further provide

[41] The high-skill employment ratio is defined as the ratio between the number of workers finishing high school and the number of workers finishing only secondary school. The correlation patterns are also robust to using finishing a college degree as an alternative measure of skill level.

[42] The year 2004 is China's Census year; therefore, more detailed data is collected for each firm (see also Brandt et al. (2014)).

[43] Indeed, while SOE-dominated industries are highly distorted, the correlation with SOE-dominated industries is actually driven by the high distortion of private firms coexisting with SOEs in these industries but not the SOEs themselves.

[44] In ongoing work, Hoang et al. (2022) investigate the impact of trade liberalization on labor market distortion in Vietnam, measured separately for men and women. Kondo et al. (2021) is a recent ongoing work that also looks at the impact of trade liberalization on labor market distortion in China, but the authors focus on heterogeneous impact along firm-level skill intensity and local supply of skills. I refer readers to these studies for more detailed analyses of the topics.

[45] This latest fact is perhaps surprising, given that workers at SOEs typically have lower marginal revenue products (Hsieh and Song (2015)). This is indeed what I find. Not conditioning on productivity, state firms have lower measured distortion. However, holding productivity fixed, SOEs are more likely to encounter friction in hiring and firing decisions. This is in line with empirical results I obtain in Section 4, where the labor supply elasticity estimated from an exogenous demand shifter for SOEs is much lower. All regression results in Section 5 are robust to excluding SOEs.

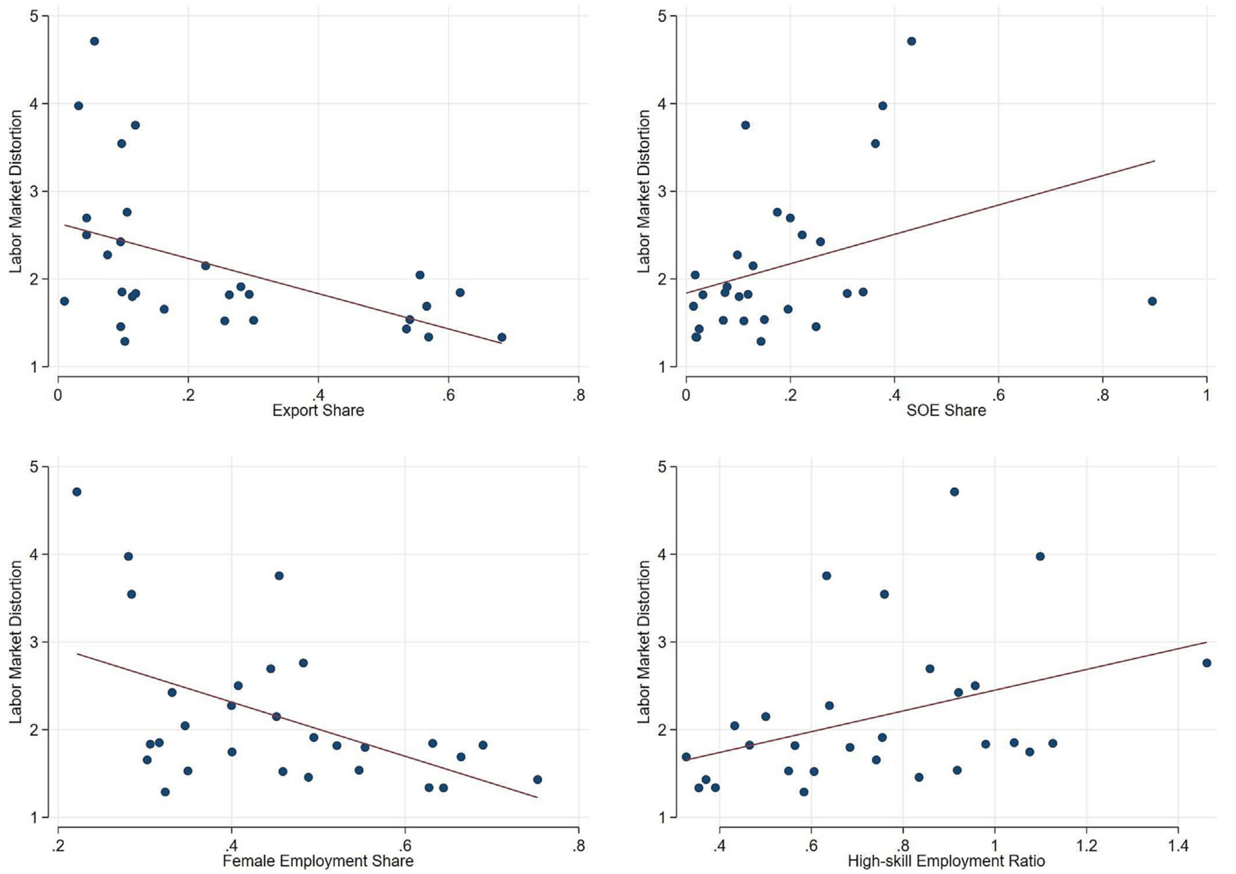

Fig. 3. Labor Market Distortion ($\tilde{\chi}_i$) and Industry Characteristics (in 2004).
Note: The figure illustrates the correlations between the measured labor market distortion ($\tilde{\chi}_i$) and (2-digit) industry characteristics in 2004. The industry characteristics include: export share, state ownership (SOE) employment 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 from 2004 because this is the only year that the employment composition information is available.

Table 2
Labor Market Distortion and Firm Characteristics.

Dependent Variable	$\tilde{\chi}_i$	$\tilde{\chi}_i$	$\tilde{\chi}_i$	$\tilde{\chi}_i$	$\tilde{\chi}_i$
	(1)	(2)	(3)	(4)	(5)
Productivity (TFPR)	6.532***	6.652***	6.708***	6.748***	7.124***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)
Employment		−0.316***	−0.285***	−0.290***	−0.353***
		(0.002)	(0.002)	(0.002)	(0.002)
Exporting			−0.332***	−0.294***	−0.192***
			(0.003)	(0.003)	(0.004)
Foreign-Owned				−0.221***	−0.123***
				(0.005)	(0.006)
SOE				0.067***	0.083***
				(0.006)	(0.007)
Local Labor Market Characteristics					
HHI^w (Employer Concentration)					0.120***
					(0.006)
Minimum Wage (Monthly)					−0.003***
					(0.000)
Observations	1,235,801	1,235,801	1,235,801	1,235,801	985,106
R-squared	0.373	0.396	0.401	0.402	0.431
Fixed Effects					
Industry (2-digit)	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes

Note: The table reports the regression results of the measured distortion ($\tilde{\chi}_i$) on firm-level characteristics. The HHI^w in column (5) is the Herfindahl-Hirschman Index of employer concentration (measured in wage bill) within a prefecture. Minimum wage data (at the prefecture level) is only available from 2000 to 2007; thus, there are fewer observations in column (5). Robust standard errors are enclosed in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

links between the nonparametric distortion measure and oligopsonistic competition in the labor market (motivated by Eq. (14) in the model), I use the local labor (and product) market Herfindahl-Hirschman Index (HHI) as an instrument to show that the non-parametric measure obtained from production approach captures key patterns of oligopsony, and is highly associated with the variation of firm's local labor market share (similar to the parametric measure obtained in the next section, even though there is no mechanical relationship between the two measures). This analysis and results are detailed in Appendix D.

4. Labor market power as endogenous distortion (parametric measure)

This section exploits an exogenous labor demand shifter to quantify the average magnitude of firms' labor market power and produce a parametric measure of labor market distortion. The removal of US trade policy uncertainty towards China (henceforth, US-China TPU), which is associated with the granting of permanent normal trade relations to China by the US in 2001, serves as a quasi-experimental labor demand shock. By comparing the responses in terms of wage and employment to the shock, this section first shows that Chinese firms' responses imply an averagely upward-sloping labor supply curve, with an average elasticity of 1.57. This result indicates that market power, on average, accounts for 76% of the overall distortion measured by the production function approach. Furthermore, the response pattern depends on the firm's local labor market wage-bill share, suggesting the existence of a strategic component of firms' competitive behavior, consistent with the theory in Section 2.

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 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 treating such shock as random. However, different from this literature's focus, my focus is on the *relative* responses in terms of wage and employment of Chinese firms to infer their labor market power.[46] Formally, the US-China TPU shock at the four-digit industry level is measured by the gap between the "Column 2" tariffs and the MFN tariffs faced by the Chinese firms.[47] Denoting this gap by τ^{TPU}, I estimate the following regression model using the OLS method:

$$log\ (w_{i,t+1}) = \beta_1 \tau_{jt}^{TPU} + \beta_2 \left(\tau_{jt}^{TPU} \times s_{ijlt}\right) + \beta_3 s_{ijlt} + \gamma_i + \gamma_{lt} + \varepsilon_{it}. \tag{33}$$

In the regression model (33), $w_{i,t+1}$ is the observed (real) wage of firm i in year $(t+1)$.[48] τ_{jt}^{TPU} is the US-China TPU shock to industry j at year t, and is computed as:

$$\tau_{jt}^{TPU} = \left\{ log\ \left(1 + \text{Column 2 Tariffs}_j\right) - log\ \left(1 + \text{MFN Tariffs}_j\right)\right\} \times PreWTO_t. \tag{34}$$

γ_i and γ_{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 location l, and in year t. This wage-bill share is an empirical counterpart of the share defined in Eq. (15). Specifically, s_{ijlt} is computed as:

$$s_{ijlt} = \frac{w_{ijlt} L_{ijlt}}{\sum_k w_{kjlt} L_{kjlt}}. \tag{35}$$

Eq. (33) is estimated with two outcome variables: the (log) wage and the (log) employment.[49] I also estimate two versions of Eq. (33): one without β_2 and β_3, and the other with β_1, β_2, and β_3. The goal of this exercise is two-fold. First, by comparing the average wage and employment responses to the common τ_{jt}^{TPU} shock, I can identify the average labor supply elasticity of Chinese manufacturing firms. This gives me an estimate of the average endogenous distortion $\tilde{\chi}_i^e = (1 + \chi_i^e)$ discussed in Section 2.1,

46 It is important to acknowledge here that the use of TPU shock for distortion measurement lies outside the product market environment posited in theory in Section 2, in the sense that the TPU shock mostly affects Chinese exporters (or potential exporters) while the theory does not model firms' export activity or export market. However, the shock is still informative about firms' behavior (exporting or not) in the labor market when they adjust to the labor demand, depending on their labor market share. The underlying assumption here is that conditioning on labor market share, a firm's export status/activity does not matter for the firm's labor market behavior. I am grateful to the editor for pointing this out.

47 "Column 2" tariffs are those 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.

48 I use average wage, computed as the ratio of wage-bill and employment, to measure the firm-level wage. Wage-bill data are 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).

49 The regression equation for the (log) employment is:
$log\ (L_{i,t+1}) = \beta_1 \tau_{jt}^{TPU} + \beta_2 \left(\tau_{jt}^{TPU} \times s_{ijlt}\right) + \beta_3 s_{ijlt} + \gamma_i + \gamma_{lt} + \varepsilon_{it}$. (33A)
One could notice that the Eq. (33) and (33A) form a seemingly unrelated regression (SUR) system. However, since the covariates are identical between the two equations, the OLS method would be equivalent to the SUR estimation method.

Table 3
Wage and Employment Response to the US-China TPU Demand Shock.

Dependent variable	$log\ (w_{i,t+1})$		$log\ (L_{i,t+1})$	
	(1)	(2)	(3)	(4)
τ_{jt}^{TPU}	−0.075***	−0.078***	−0.118***	−0.159***
	(0.021)	(0.024)	(0.044)	(0.044)
Market Share $(s_{ijlt}) \times \tau_{jt}^{TPU}$		0.035*		0.220***
		(0.018)		(0.024)
Market Share (s_{ijlt})		0.011**		0.213***
		(0.005)		(0.007)
Observations	1,235,801	878,278	1,235,801	878,278
R-squared	0.711	0.734	0.897	0.911
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year (4-digit)	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (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 Eq. (35), and τ_{jt}^{TPU} is the trade policy uncertainty (TPU) shock. Columns (2) and (4) have fewer observations because of the use of lagged shares. Standard errors in parentheses are clustered two-way at the firm level and industry-by-year level (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

which can be reliably attributed to labor market power. Second, by allowing 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 et al. (2022), 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 et al. (2019). In the context of labor market power in developing countries, Amodio and de Roux (2021) is a recent study that adopts a similar approach in Colombia.[50]

Identification of Eq. (33) is obtained by comparing changes in wage and employment of firms within the same location yet exposed to differential labor demand shocks due to their industry affiliations. The inclusion of location-by-year fixed effects controls for any common time-varying local labor market shocks. 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 β_1^h and β_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 3 reports the regression results of Eq. (33). Columns (1) and (2) report results for Eq. (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 τ_{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" τ_{jt}^{TPU} leads to a 0.075 point increase in wage and a 0.118 point increase in employment. On average, the change in τ_{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 1.88% and 2.95% 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., $\frac{dlog(w)}{dlog(\tau^{TPU})}$, is about half the size of the response of the employment, i.e., $\frac{dlog(L)}{dlog(\tau^{TPU})}$. This result, in turn, indicates the *average* labor supply elasticity faced by a firm is 1.57. Computing the endogenous distortion from this labor supply elasticity implies the magnitude of 1.64. Compared with my average estimates from the production function approach in Section 3, this endogenous distortion accounts for 76% of the overall nonparametric distortion. This is one of the key findings 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 β_2^h. 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.[51] 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:

[50] Amodio and de Roux (2021) construct a firm-level trade shock due to the trade composition of each Colombian firm and find an average labor supply elasticity very similar in magnitude to what I find here for China.

[51] This result resonates with the findings by Berger et al. (2022), in which the authors exploit changes in corporate taxes, rather than international trade shocks, to identify the endogenous distortion for the US.

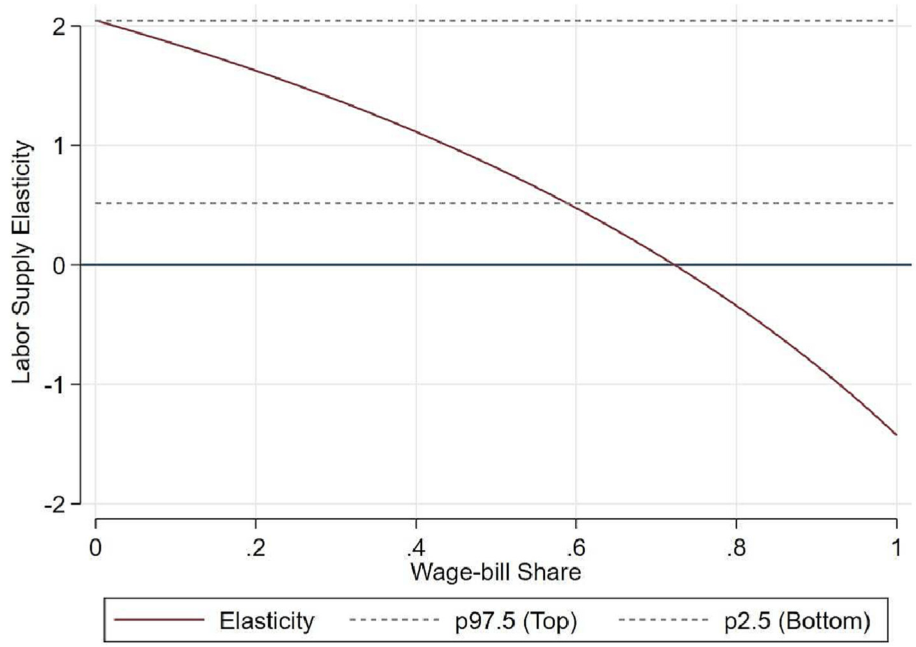

Fig. 4. Labor Supply Elasticity by Local Labor Market Wage-bill Share.
Note: The figure illustrates the labor supply elasticity ($\varepsilon(s_{ijlt})$) as a function of local labor market share in Eq. (36), with the estimated parameters obtained from regression Eq. (33). $p2.5$ and $p97.5$ are the 2.5th and 97.5th percentiles, with the values of 0.51 and 2.04 respectively.

$$\varepsilon\left(s_{ijlt}\right) = \frac{dlog\left(L_{i,t+1}\right)}{dlog\left(w_{i,t+1}\right)} = \frac{\frac{dlog\left(L_{i,t+1}\right)}{d\left(\tau_{jt}^{TPU}\right)}}{\frac{dlog\left(w_{i,t+1}\right)}{d\left(\tau_{jt}^{TPU}\right)}} = \frac{\beta_1^L + \beta_2^L s_{ijlt}}{\beta_1^W + \beta_2^W s_{ijlt}}. \tag{36}$$

Given the formula in Eq. (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 decreased from 0.31 in 1998 to 0.17 in 2007. Plugging these numbers into Eq. (36), an average share of 0.31 implies the value of $\varepsilon(0.31)$ is 1.35. An average share of 0.17 implies the value of $\varepsilon(0.17)$ is 1.69. Firms with a very small labor market share, 0.01 for instance, would face an elasticity of 2.01, while firms that account for a very large share of the local labor market, 0.5 for instance, would face a labor supply elasticity of 0.81. As a consequence, the endogenous distortion implied by the estimates in columns (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, Fig. 4 graphs the computed elasticity based on Eq. (36).[52] The results in Table 3 provide clear evidence that an endogenous form of labor market distortion exists, i.e., labor market power. Such endogenous distortion accounts for almost 76% of the overall distortion measured by the production function approach in Section 3. Furthermore, the distortion significantly depends on a firm's local labor market share and permits a parametric measure of the distortion, as shown below.

A Measure of Share-Dependent Endogenous Distortion I use the share-dependent labor supply elasticity calculated by Eq. (36) to compute a parametric measure of share-dependent distortion. More specifically, from the labor supply elasticity in Eq. (36), this measure is computed as:

$$\tilde{\chi}^e\left(s_{ijlt}\right) = 1 + \frac{1}{\varepsilon\left(s_{ijlt}\right)}. \tag{37}$$

The measure $\tilde{\chi}^e(s_{ijlt})$ in Eq. (37) is consistent with the theory in Section 2. For this measure, its only variation source comes directly from the share s_{ijlt}. In other words, measuring the distortion from the reduced-form approach as in Eq. (37) assumes that the structural parameters of the labor supply system in Eqs. (6)–(7) are constant across industries and years. Despite this strong assumption, the measure is still useful. It can serve two purposes: (1) it can help to cross-validate the measure of the distortion

[52] The estimated coefficients restrict the ability to infer the elasticity for a firm with labor market share $s_{ijlt} \geq 0.723$, i.e., elasticity is negative. 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, less than 13% firm-year observations dominate the whole market, and I exclude these firms in my subsequent analyses when it involves the endogenous distortion measured by the regression approach in this section.

from the production function approach in Section 3, and (2) it explicitly illustrates how the response of local labor market share to trade shocks translates directly to the response in labor market distortion and provides an oligopsony narrative for trade effects as in the model.[53,54] Appendix I provides more descriptive features of this measure, and Appendix D correlates the parametric measure with the nonparametric one obtained in Section 3.

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 5.1, I briefly describe changes in China's trade policy regime associated with its accession to WTO in 2001. In Section 5.2, I specify regression models and present associated results.

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.[55] This paper focuses on the impact of lowering the tariff barriers. Specifically, I consider two policy instruments: the output tariff (τ^O) and the input tariff (τ^I), the empirical counterparts of the theoretical policy instruments in Section 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:

$$\tau_j^I = \sum_m a_{mj} \tau_m^O, \tag{38}$$

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

In the left panel of Fig. 5, I plot the changes in the average and interquartile range of applied tariffs. Table J3 summarizes China's tariff evolution over the sample period from 1998 to 2007. The cutoff event was at the end of 2001 when China's official status in WTO became effective. As shown in Fig. 5 and reported in Table J3, along with a reduction in the average 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 the evidence for an exogenous source 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), De 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. The standard deviation decreased from 3% to 2% in respective years.[56]

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 example, as in Pavcnik (2002), Amiti and Konings (2007), Topalova and Khandelwal (2011), and Brandt et al. (2017). The specification is as follows:

$$log\left(\tilde{\chi}_{ijlt}\right) = \gamma_O \times \tau_{j,t-1}^O + \gamma_I \times \tau_{j,t-1}^I + \gamma_i + \gamma_{cic2,t} + \gamma_{lt} + \varepsilon_{ijlt}. \tag{39}$$

In Eq. (39), the dependent variable is the (log) measured labor market distortion. $\tau_{j,t-1}^O$ and $\tau_{j,t-1}^I$ are the one-year *lagged* output and input tariffs for industry j, computed at four-digit and three-digit aggregation level respectively. γ_i controls for firms' fixed effects, and γ_{lt} controls for location-by-year fixed effects, similar to the regression in Eq. (33). Since my production function

[53] It is important to emphasize that the objects recovered in Eqs. (36)–(37) are reduced-form *general equilibrium* objects, as does the measure computed in Section 3. More specifically, the implied labor supply elasticity and distortion measured using the regression approach already capture the best responses of competitors within the same labor market. However, as pointed out by Berger et al. (2022), if one wants to recover structural parameters of the model proposed in Section 2 (such as θ and η) out of the reduced-form measured firm-level distortion, one needs to make important adjustments to account for strategic responses of competitors.

[54] There is no mechanical correlation at the firm level between the two measures of distortion. Notice that in Eq. (32), the wage bill of each firm enters the denominators of the ratios on the right-hand side. On the other hand, distortion is an increasing function of wage-bill share in Eq. (37).

[55] Along with the reduction in import tariffs, China also made commitments to reduce other non-tariff barriers upon WTO accession substantially. See Brandt and Rawski (2008) and Brandt et al. (2017) for more institutional contexts of this event.

[56] 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 J3. The correlation between output and input tariff changes across 4-digit industries is 0.59, and including them either individually or simultaneously almost does not change the estimates.

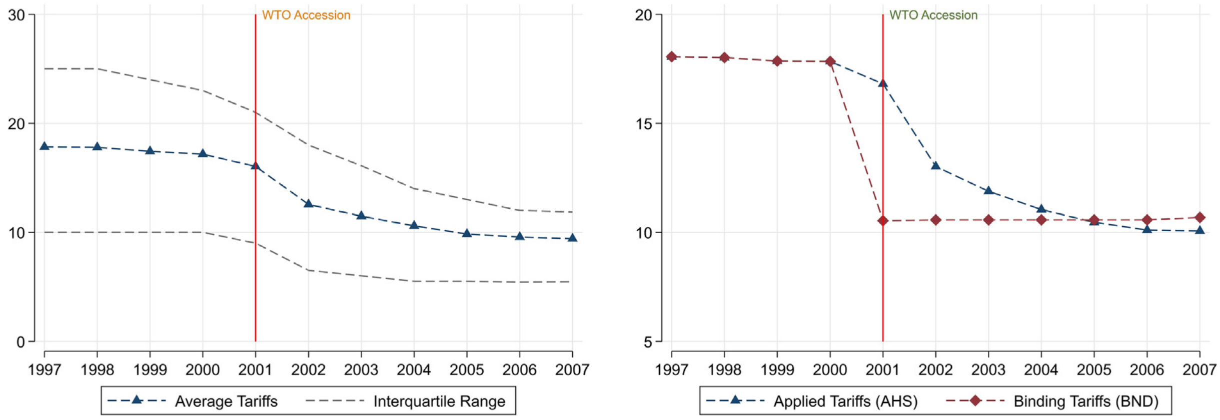

Fig. 5. China's Tariffs Evolution in the Pre-Post WTO Periods.
Note: The left panel illustrates changes in the average and interquartile range of applied tariffs across industries and over time. The right panel shows changes in the (average) applied tariffs (AHS) versus binding tariffs (BND), which are used as instruments.

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.[57] The coefficients of interest are γ_O and γ_I.[58] 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 the four-digit (or three-digit) industry level. Across all the specifications, standard errors are clustered two-way at the firm and industry-by-year levels.

In my baseline estimation, Eq. (39) is estimated with the OLS method. Although a large set of fixed effects is included in Eq. (39), there might still be an endogeneity concern about the industry-level tariff changes. In my theoretical analysis, productivity is a determinant of firm-level labor market distortion. When China joined 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 industries 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 applied tariff and estimate Eq. (39) with the 2SLS method. The right panel of Fig. 5 illustrates the co-evolution of the average applied and binding tariff over time. 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.

Other identification concerns might arise from the supply side of the labor market. In Eq. (39), the inclusion of location-by-year fixed effects (γ_{lt}) absorbs any *common* time-varying local labor supply shocks. The identification assumption here is that the changes in tariffs ($\Delta\tau^O_{jt}$ and $\Delta\tau^I_{jt}$) are not correlated with unobserved labor supply shocks at *specific* (4-digit) industry $j \times$ location l. There are two potential threats to this identification assumption. First, these unobserved supply shocks could arise due to an interaction effect between labor market regulation and trade policy changes. Second, these unobserved supply shocks could be caused directly by trade policy, via trade affecting workers' long-run career choice, and thus the aggregate labor supply elasticity to certain (jl) markets. In the latter case, the threat is not about endogeneity but about the interpretation of the effect of trade policy on labor market distortion.

On the first threat, it is unlikely that prefecture-level labor market regulation is tailored in a way that is correlated with tariff changes at the 4-digit industry level. Most important labor market regulation changes in China during this period, for example, the gradual relaxation of the hukou system, are at the location level rather than the specific industry-location level (Fan, 2019). At most, if there were some tailoring, one would expect that policymakers might be able to do so at the 2-digit industry $\times$ location level. To check if this is a potential threat, I re-estimate my main regressions, including 2-digit industry $\times$ location $\times$ year fixed effects (to replace the combination of 2-digit industry $\times$ year and location $\times$ year fixed effects). I find that my main empirical results (presented below) remain unaffected and report these results in Table H1 of Appendix H. Furthermore, the IV strategy I use for trade policy has also somewhat alleviated concern about the potential influence of policymakers. Another likely supply-side concern (not exactly labor regulation) is the privatization wave in China during this period that could be industry-location specific and serves as a local labor supply shock. I drop firms that have ever had SOE ownership and report regression results in the same table. I find my results remain robust here as well.

[57] This additional fixed-effect term turns out to be important since I observe some diverging trends in measured distortion and productivity at the 2-digit industry level.

[58] An essential assumption for identification of the causal impact of tariff changes on the labor market distortion using Eq. (39) is the constant treatment effect assumption, in which I assume that the causal effects of tariffs are constant across firms, location, industry and time.

Table 4
Impact of Tariff Changes on Entry, Exit, and Labor Market Share.

Dependent Variable	Entry		Exit		Market Share	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Output Tariffs ($\tau^{O}_{j,t-1}$)	0.109***	0.083**	−0.096***	−0.080***	−0.124	−0.209
	(0.037)	(0.042)	(0.027)	(0.028)	(0.199)	(0.235)
Input Tariffs ($\tau^{I}_{j,t-1}$)	−0.785***	−0.891***	0.337**	0.290**	4.656*	6.304*
	(0.256)	(0.332)	(0.131)	(0.141)	(2.546)	(3.251)
Observations	1,235,801	1,235,801	1,235,801	1,235,801	1,235,801	1,235,801
R-squared	0.524	.	0.742	.	0.927	.
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Two-way						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (39) with three dependent variables: (1) indicator for a firm entry, (2) indicator for a firm exit, and (3) log of labor market share ($\log(s_{ijlt})$), defined in Section 4. 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. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

On the second threat that affects the interpretation of the (competition) effect of trade policy, the threat only applies if trade policy changes affect career expectation and thus the long-run decision of workers to move towards certain industries relative to others. This will affect the aggregate labor supply elasticity in certain industries and, in turn, the measured firm-level distortion.[59] Nonetheless, this is unlikely to happen at the 4-digit industry level (within 2-digit industries) because workers must know about these narrow industries' potential growth and correctly anticipate that trade policy will affect such growth in the long run. If workers are making these calculations at the 2-digit industry level, results in Table H1 demonstrate that the change in aggregate labor supply elasticity cannot account for the effect of trade policy on labor market distortion. Having elaborate on concerns about identification, I next report the main empirical results.

Local Entry, Exit, and Labor Market Share To begin with, Table 4 reports the estimation results with three dependent variables: (1) indicator for a firm entry, (2) indicator for a firm exit, and (3) log of labor market share ($\log(s_{ijlt})$), defined in Section 4. Columns (1)–(4) show that entry and exit patterns across local labor markets respond significantly to tariff changes. In particular, lowering output tariffs decreases the probability of a firm entering and increases the probability of a firm exiting the local market. On the other hand, lowering input tariffs increases the probability of entry while reducing the probability of exit.[60] These results resonate with the findings in previous literature where plant survival rate, growth, and consequential labor market outcomes are associated with trade shocks (Bernard et al. (2006), Asquith et al. (2019)). Labor market share also responds to trade policy changes. Specifically, in columns (5)–(6), lowering output tariffs is negatively associated with the labor market share of a firm, while lowering input tariffs is positively associated with this firm-level variable. However, the estimated coefficients are only significant for input tariff reductions, implying a stronger influence of input tariffs on labor market share. Overall, Table 4's results are strongly consistent with the theory's prediction, which lends empirical support for the modeling approach proposed in Section 2.2.

Labor Market Distortion Table 5 reports the estimation results for this paper's primary outcomes of interest. Columns (1)–(4) show the results of the regression Eq. (39), using the (log) overall nonparametric distortion measured in Section 3 as the dependent variable. Across the columns, which use two complementary 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. In contrast, a reduction in the input tariff leads to decreased measured distortion.

Quantitatively, however, only input tariffs have a strong and significant impact on the distortion. Specifically, based on the OLS estimates, a one percentage point decrease in input tariffs leads to a 0.539 percentage point reduction in the distortion. IV estimates imply a 0.603 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 to 2007, these estimation results

[59] This threat is not about workers moving to certain industries because of higher wages. Rather, it is about observing the same (realized) change in wages, workers are more willing to move to certain industries rather than others because of trade policy changes. In the model, this translates to the Frisch elasticity of labor supply being endogenous to trade policy.

[60] It is nevertheless important to emphasize that the definition of entry and exit here depends on the sample. That is, one should interpret these results as entering and exiting the working sample, which in this case involves all firms with sales above 5 million Renminbi (≈ 700,000 US Dollars in current price). My cleaning procedure keeps the size threshold consistent, and these results remain strongly robust to less stringent cleaning procedures.

Table 5
Impact of Tariff Changes on the Labor Market Distortion.

Dependent Variable	Nonparametric Measure $log\left(\tilde{\chi}_{ijlt}\right)$				Parametric Measure $log\left(\tilde{\chi}^e(s_{ijlt})\right)$			
	OLS	OLS	OLS	IV	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Output Tariffs ($\tau^O_{j,t-1}$)	−0.011		−0.037	−0.029	−0.025		−0.036*	−0.036*
	(0.058)		(0.057)	(0.053)	(0.021)		(0.019)	(0.021)
Input Tariffs ($\tau^I_{j,t-1}$)		0.492*	0.539**	0.603**		0.225*	0.264*	0.336**
		(0.265)	(0.259)	(0.289)		(0.135)	(0.135)	(0.155)
Observations	1,235,801	1,235,801	1,235,801	1,235,801	1,074,093	1,074,093	1,074,093	1,074,093
R-squared	0.758	0.758	0.758	.	0.668	0.668	0.668	.
Fixed Effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Two-way								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (39) with two dependent variables: $log\left(\tilde{\chi}_{ijlt}\right)$ and $log\left(\tilde{\chi}^e(s_{ijlt})\right)$. 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 4 are trimmed in columns (5)–(8). Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

suggest that the average labor market distortion decreased by 3% as a consequence of China's reduction in the input tariffs (using IV estimates). Compared with input tariffs, output tariff reductions had a negligible and insignificant effect on labor market distortion.

Columns (5)–(8) estimate Eq. (39) using the (log) share-dependent parametric distortion measured by the regression approach in Section 4 as the dependent variable. These columns aim to compare the results between the two different measures of labor market distortion. Consistent with the results in columns (1)–(4), estimated coefficients of tariffs have the same signs. In columns (7)–(8), however, the coefficients of both tariffs are 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 0.036 percentage point increase in the share-dependent distortion in the OLS estimates, compared to the same estimate of 0.036 in the IV estimates. On the other hand, a one percentage point decrease in the input tariffs leads to a 0.264 and 0.336 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 (7) and (8) suggest that the output tariff reduction led to a 0.25% increase in the distortion, while the input tariff reduction led to a 1.68% decrease in the distortion (using IV estimates). Remarkably, these estimates are very similar and in the same order of magnitude compared to the production function measure of the distortion, despite employing two totally different approaches to measurement. The results imply a common underlying economic mechanism driving the responses of measured distortion to trade policy changes, which further supports the presence of competitive effects of trade in the labor market.

Robustness to Using an Alternative Distortion Measure (Bau and Matray (2020)**)** In addition to the main empirical results in Table 5, I also further check the robustness of these results with an alternative measure recently used in the misallocation literature, more specifically in Bau and Matray (2020). Bau and Matray (2020) also exploit the intuition from the production function approach to measure distortion in the capital and labor market for India's manufacturing sector and investigate how foreign investment liberalization affects such distortion. In their measurement, the (revenue) production function is assumed to be Cobb-Douglas and, thus, does not require invoking production function estimation techniques (as well as associated assumptions). I elaborate on the measure and corresponding results in Table E1-E2 of Appendix E. All results in Table 5 remain strongly robust, although the magnitudes of the trade policy effects using this alternative measure are larger, highlighting the importance of considering production function heterogeneity and the effects of trade on it.

Markup It is theoretically possible that changes in labor market distortion in response to trade policy are the results of changes in product market distortion, and thus trade affects competition in the labor market through the intensive margin. This happens when the dimensions of competition in the product market and labor market are not entirely orthogonal. For instance, in MacKenzie (2019)'s model, trade shocks can induce reallocation in an oligopolistic product market and thus induce reallocation in the labor market. If this is the case, one would expect trade policy's effects on markup and labor market distortion to move in the same direction.

Previous literature on trade and markup offers some evidence going against this mechanism. For example, in the case of India's manufacturing sector, De Loecker et al. (2016) find that trade liberalization leads to a net increase in firm-level markup, working mainly through the reduction of input tariffs. Similarly and more closely related to my paper, in the case of China's manufacturing sector, Brandt et al. (2017) find that trade liberalization also increases Chinese firms' markup on net. If trade policy affecting markup is the main mechanism that leads to changes in competition in the labor market, we would have expected that labor market distortion increases on net as a result of the liberalization. My empirical results on labor market distortion suggest otherwise and thus render evidence against the markup mechanism.[61]

Heterogeneous Effects Motivated by across-industry correlations documented in Section 3.3, I perform a preliminary heterogeneity analysis intending to shed some light on where the effect of trade policy is most prominent in influencing labor market distortion. To do so, measures of 2-digit industry's export share, SOE (employment) share, female employment share, and high-skill employment ratio are interacted with tariff shocks, and Eq. (39) is re-estimated, including these interaction terms. I report these results (IV estimates) in Appendix Table G1. The interaction terms make the estimates using the nonparametric measure noisier, while the estimates using the parametric measure remain precise. Across all specifications, a robust finding is that while the effect of output tariff on distortion is concentrated in domestic-oriented industries (distortion increases more), the effect of input tariff on distortion is concentrated in more export-oriented industries (distortion decreases more). Another consistent but perhaps less robust finding is that SOE-dominated industries see smaller effects of both output and input tariffs, i.e., a firm's distortion in these industries is less impacted by tariff changes. I do not find consistent heterogeneous effects of the trade policy across industries with different intensities in female or skilled workers. I leave further consideration on the topics for future study.

Discussion Overall, empirical results in this section confirm the theoretical predictions on the relationship between trade policy and labor market distortion. For China, the estimates suggest that even though lowering output tariffs has a tendency to increase the distortion, its effect is negligible. On the other hand, lowering input tariffs reduces labor market distortion, with the magnitude of the overall effect amounting to 3% based on my preferred estimates.

To put this estimate in perspective, the average competitive effect of trade policy estimated above can be thought of as an improvement in labor productivity or real wages, holding everything else fixed. Tombe and Zhu (2019) estimate a quantitative model with goods- and labor-market frictions and find that changes in international trade cost account for only 4.5% of the overall 57.1% labor productivity growth in China during the period 2000–2005. Even though Tombe and Zhu (2019)'s model does not feature strategic competition in the labor market that is part of labor market frictions, the estimate here implies that the effect of trade policy working through competition in the labor market is equivalent to two-thirds of the overall effect estimated by Tombe and Zhu (2019).[62]

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 effect of trade policy on distortion in the labor market, providing clear predictions based on this model. Second, I propose two complementary strategies to measure labor market distortion consistently 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 firms' endogenous entry and exit across local labor markets induced by trade shocks.

My theoretical and empirical results have several implications for understanding 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 et al. (2012), might be affected by the presence of such distortion and its endogenous response to trade.

Data availability

pham, hoang (2023), "Trade Reform, Oligopsony, and Labor Market Distortion: Theory and Evidence ", Mendeley Data, V1, doi: 10.17632/6pkrbn2yct.1 (Original data) (Mendeley Data)

[61] Even though the Chinese firm-level data do not contain firm-level price information, making it challenging to reliably estimate markup, in Appendix F, I exploit my revenue production function estimation in Section 3.1 and impose the constant return-to-scale (CRS) assumption to infer firm-level markup. I then regress this measured markup on China's trade policy changes as in Eq. (39). I find similar results that China's trade liberalization has led to an increase in markup on net. In addition, the magnitude of the effect on markup (based on my measurement) is an order of magnitude smaller than the effect on labor market distortion. I also re-run regressions in Table 5, adding the measured markup as control, and find that all results remain very similar, although the point estimates using the nonparametric measure become slightly noisier.

[62] However, this comparison is not exactly apple-to-apple. Exact accounting for the labor market competitive effect of trade policy would require explicitly embedding the strategic labor competition into a general equilibrium model as in Tombe and Zhu (2019).

Declaration of Competing Interest

None

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Appendix A. Theory Appendix

A.1. Key model results

First-order conditions (FOC) First-order condition of a firm's profit maximization problem:

$$\frac{MRPL(z)}{w(z)} = \frac{\frac{\gamma-1}{\gamma} zp(z)}{w(z)} = 1 + \frac{1}{\varepsilon(s(z))}, \tag{A1}$$

where $\varepsilon(s(z))$ is the elasticity of labor supply and has value[63]:

$$\varepsilon(s(z)) = \frac{1}{\frac{1}{\eta} + s(z)\left(\frac{1}{\theta} - \frac{1}{\eta}\right)}. \tag{A2}$$

Equilibirum wages We can also rewrite $MRPL(z)$ as:

$$\begin{aligned} MRPL(z) &= z^{\frac{\gamma-1}{\gamma}} L(z)^{-\frac{1}{\gamma}} \mathbf{P}^{\frac{\gamma-1}{\gamma}} \Xi \\ &= z^{\frac{\gamma-1}{\gamma}} w(z)^{-\frac{\theta}{\gamma}} s(z)^{-\frac{\Psi}{\gamma}} \Lambda \end{aligned} \tag{A3}$$

where $\Lambda = \overline{\phi}^{-\frac{1}{\gamma}} \mathbf{W}^{\frac{\theta-\phi}{\gamma}} \mathbf{P}^{\frac{\gamma-1}{\gamma}} \Xi > 0$ and $\Psi = \frac{\eta-\theta}{1+\eta} > 0$.[64] Combining (A1) and (A3), we can derive the following equilibrium relationship:

$$\begin{aligned} w(z) &= \left(\frac{1}{\left[\left(1+\frac{1}{\eta}\right) + \left(\frac{1}{\theta} - \frac{1}{\eta}\right) s(z)\right] s(z)^{\frac{\Psi}{\gamma}}} \right)^{\frac{\gamma}{\gamma+\theta}} z^{\frac{\gamma-1}{\gamma+\theta}} \Lambda^{\frac{\gamma}{\gamma+\theta}} \\ &= m(s(z))\ddot{z}. \end{aligned} \tag{A4}$$

Here, we denote $m(s(z)) = \left(\frac{1}{\left[\left(1+\frac{1}{\eta}\right) + \left(\frac{1}{\theta} - \frac{1}{\eta}\right) s(z)\right] s(z)^{\frac{\Psi}{\gamma}}} \right)^{\frac{\gamma}{\gamma+\theta}}$ and $\ddot{z} = z^{\frac{\gamma-1}{\gamma+\theta}} \Lambda^{\frac{\gamma}{\gamma+\theta}}$. It is straightforward to verify that $m(s(z))$ is a *strictly decreasing* function in $s(z)$, while $\ddot{z}$ is a *strictly increasing* function in z and Λ (since $\theta < \eta$, $\Psi > 0$, and $\gamma > 1$). This equation illustrates a key property of the model that makes the following proofs work. Finally, FOCs of all firms form the following system of equations in the vector form:

$$\overline{w}(z) = \overline{m}(s(z))^T \overline{\ddot{z}} \tag{A5}$$

[63] The expression for $\varepsilon(s(z))$ equation can be derived straightforwardly from the labor supply curve in Eq. (11).

[64] This can be shown by noticing that $L(z) = \overline{\phi} w(z)^{\eta} W_n^{\theta-\eta} W^{\phi-\theta} = \overline{\phi} \frac{w(z)^{\eta}}{w(z)^{\eta-\theta}} \frac{w(z)^{\eta-\theta}}{\left[\sum_{z' \in Z_n} w(z')^{1+\eta}\right]^{\frac{\eta-\theta}{1+\eta}}} W^{\phi-\theta} = \overline{\phi} w(z)^{\theta} s(z)^{\frac{\eta-\theta}{1+\eta}} W^{\phi-\theta}$.

A.2. Profit monotonicity

The *profit monotonicity* condition is stated as follows:

$$\Pi^K\left(z^{(k)}\right) \geq \Pi^{K+1}\left(z^{(k)}\right) \geq \Pi^{K+1}\left(z^{(k+1)}\right). \tag{A6}$$

The second inequality is proved first. This inequality states that, given the same market condition, more productive firms always command higher profits than less productive firms (recall the productivity ranking $z^{(1)} > \ldots > z^{(k)} > z^{(k+1)}$). The proof is straightforward by deduction: given the aggregate equilibrium conditions, the more productive firm $z^{(k)}$ can always hire the same amount of workers, pay the same wages, and charge at least the same price as the less productive firm $z^{(k+1)}$, and makes more profit (see also in Eaton et al. (2012)). (Q.E.D).

The first inequality states that for the same firm with productivity $z^{(k)}$, the firm is more profitable if there are fewer 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 equilibrium profit of firm z as:

$$\begin{aligned}\Pi(z) &= \left[\frac{\gamma}{\gamma-1}\left(1+\frac{1}{\varepsilon(s(z))}\right)-1\right]w(z)L(z)-f \\ &= w(z)^{\theta+1}\left[\frac{\gamma}{\gamma-1}\left(1+\frac{1}{\eta}\right)+s(z)\left(\frac{1}{\theta}-\frac{1}{\eta}\right)-1\right]s(z)^{\frac{\eta+\theta}{1+\eta}}\overline{\phi}W^{\phi-\theta}-f\end{aligned} \tag{A7}$$

Based on this profit function, it can be shown that for $z' \neq z$[65]:

$$\frac{\partial \Pi(z)}{\partial w(z')} \leq 0 \qquad \text{and} \qquad \frac{\partial^2 \Pi(z)}{\partial w(z)\partial w(z')} \geq 0. \tag{A8}$$

The left inequality asserts that a lower wage on the part of a local competitor increases the profit of firm z. This is because lower $w(z')$ reduces the employment of firm z' and thus allow firm z to set lower wage to attract workers. The right inequality asserts that the lower wage of a local competitor induces firm z to decrease its wage (wage complementarity).

From inequalities in (A8), by removing firm $z^{(k+1)}$ and essentially making its wage $w\left(z^{(k+1)}\right) \to 0$, all incumbent firms in the market becomes more profitable, and hence, $\Pi^K\left(z^{(k)}\right) \geq \Pi^{K+1}\left(z^{(k)}\right)$. (Q.E.D).

A.3. Proposition 1

Proposition 1 is proved in two steps. First, we show that conditioning on a fixed number of firms K, there exists a unique equilibrium vector of wages (and associated vectors of employment and shares) in the local labor market.

Existence Expression in Eq. (A4) is sometimes sufficient to bound the wages and allows us to invoke Brouwer's fixed point theorem directly for existence. However, in this case, due to the presence of CES demand ($\gamma < \infty$), wages cannot be bounded as $s(z) \to 0$. It is thus useful to rewrite the system of equations in shares. Equations in (A4) and (A5) are equivalent to:

$$\begin{aligned}&w(z)^{\eta+1} = m(s(z))^{\eta+1}\ddot{z}^{\eta+1} \\ &\ldots\end{aligned} \tag{A9}$$

Sum up these equations vertically across all firms, we have:

$$\sum_z w(z)^{\eta+1} = \sum_z m(s(z))^{\eta+1}\ddot{z}^{\eta+1} \tag{A10}$$

Divide each equation in (A9) to (A10) and using the share expression in Eq. (15), we obtain[66]:

$$s(z) = \frac{m(s(z))^{\eta+1}\ddot{z}^{\eta+1}}{\sum_z m(s(z))^{\eta+1}\ddot{z}^{\eta+1}} \tag{A11}$$

[65] See also similar conditions and arguments for the oligopoly model in Eaton et al. (2012). Derivations for these inequalities are available upon request.

[66] Notice that this equation is free of aggregate variables contained in Λ and vector of equilibrium shares only depend on the set of firms' productivity since Λ cancels out.

From this equation, we can derive the lower bound of $s(z)$. Let $s_{min} = s\left(z^{(K)}\right)$ such that $s_{min} \le s(z) \quad \forall z$. Recall that since $m(.)$ is strictly decreasing in $s(z)$ and $\eta > 0$, we must have:

$$s_{min} = \frac{m(s_{min})^{\eta+1}\ddot{z}_{min}^{\eta+1}}{\sum_z m(s(z))^{\eta+1}\ddot{z}^{\eta+1}} \ge \frac{m(s_{min})^{\eta+1}\ddot{z}_{min}^{\eta+1}}{m(s_{min})^{\eta+1}\left[\sum_z \ddot{z}^{\eta+1}\right]} = \frac{\ddot{z}_{min}^{\eta+1}}{\sum_z \ddot{z}^{\eta+1}} = s^* > 0 \tag{A12}$$

As a result, s^* is the lower bound of labor market share.

Define a set S as: $\bar{s} \in [s^*, 1]^K$ and $\sum_{z \in Z_K} s(z) = 1$. By construction, S is a nonempty, compact, and convex set. Define a function $F : S \mapsto S$ as follow:

$$F_z(\bar{s}) = \frac{m(s(z))^{\eta+1}\ddot{z}^{\eta+1}}{\sum_z m(s(z))^{\eta+1}\ddot{z}^{\eta+1}} \qquad \forall z \in Z_K \tag{A13}$$

Function $F : S \mapsto S$ is a continuous function mapping from S to itself. Thus, Brouwer's fixed point theorem applies, and the existence result is established. (Q.E.D).

Uniqueness Suppose that there exist two different vectors of wages satisfying the system of Eq. (A5). As a result, they are characterized by two different vectors of shares $(s'_1, \ldots, s'_K)$ and $(s''_1, \ldots., s''_K)$. Hereafter, the productivity ranking of firms will not matter for the proof; thus, I index firms by subscript k rather than productivity z. It follows that $s'_\kappa \neq s''_\kappa$ for some $1 \le \kappa \le K$.

The following proof closely mimics the proof proposed by Kucheryavyy (2012) for an oligopolistic competition model.[67] Without loss of generality, suppose that $s'_\kappa > s''_\kappa$. It follows from Eq. (A4) that $w'_\kappa < w''_\kappa$ since $m'(s_\kappa) < 0$.[68] It is also follows that $\left(\frac{w'_\kappa}{w''_\kappa}\right)^{\eta+1} < 1$.

For any $k = 1, \ldots, K$, let $r_k = \left(\frac{w'_k}{w''_k}\right)^{\eta+1}$. We reorder firms by index k such that $r_k \le r_l$ for any $k \le l$. Since $r_\kappa < 1$ for some κ, we must have $r_1 < 1$. For any k, denote:

$$\begin{aligned} d'_k &\equiv (w'_k)^{\eta+1} + \ldots + (w'_K)^{\eta+1} \\ d''_k &\equiv (w''_k)^{\eta+1} + \ldots + (w''_K)^{\eta+1} \end{aligned} \tag{A14}$$

We will show that $\frac{d'_k}{d''_k} < r_1 \quad \forall k \ge 2$.

First, consider the case where $k = 2$. By definition and from the share expression in Eq. (15), $r_1 < 1$ is equivalent to $s'_1 > s''_1$ and thus:

$$\begin{aligned} &\frac{(w'_1)^{\eta+1}}{(w'_1)^{\eta+1} + d'_2} > \frac{(w''_1)^{\eta+1}}{(w''_1)^{\eta+1} + d''_2} \\ &\Leftrightarrow \frac{d'_2}{d''_2} < \left(\frac{w'_1}{w''_1}\right)^{\eta+1} = r_1 \end{aligned} \tag{A15}$$

Next, suppose that $\frac{d'_k}{d''_k} < r_1$ for some $k \ge 2$, we will show that $\frac{d'_{k+1}}{d''_{k+1}} < r_1$. By construction, $\frac{d'_k}{d''_k} < r_1$ is equivalent to:

$$\begin{aligned} &\frac{(w'_k)^{\eta+1} + d'_{k+1}}{(w''_k)^{\eta+1} + d''_{k+1}} < r_1 \\ &\Leftrightarrow (w'_k)^{\eta+1} + d'_{k+1} < r_1\left((w''_k)^{\eta+1} + d''_{k+1}\right) \end{aligned} \tag{A16}$$

[67] The proof by Kucheryavyy is provided on his website. I am extremely grateful to Oleg Itskhoki and Konstantin Kucheryavyy for referring me to this proof.

[68] An attentive reader will notice that $\ddot{z}$ is a function of $\mathbf{W}$, which in turn is function of s_κ itself. However, recall that because there is a continuum of local labor markets, vector of shares $\bar{s}_k$ within a local labor market has no influence on the aggregate wage index, and thus, firms take this term as given. Alternatively, one can make this proof works by directly using decreasing property of function $m(.)$ in the system of Eqs. (A11) and (A13) since the influence of aggregate variables in Λ cancels out.

Divide both sides by d'_{k+1}, we have:

$$\begin{aligned} &\frac{(w'_k)^{\eta+1}}{d'_{k+1}} + 1 - r_1 \frac{(w''_k)^{\eta+1}}{d'_{k+1}} < r_1 \left(\frac{d''_{k+1}}{d'_{k+1}}\right) \\ \Leftrightarrow\ & 1 + \frac{(w'_k)^{\eta+1}}{d'_{k+1}} \left(1 - r_1 \frac{(w''_k)^{\eta+1}}{(w'_k)^{\eta+1}}\right) < r_1 \left(\frac{d''_{k+1}}{d'_{k+1}}\right) \\ \Leftrightarrow\ & 1 + \frac{(w'_k)^{\eta+1}}{d'_{k+1}} \left(1 - \frac{r_1}{r_k}\right) < r_1 \left(\frac{d''_{k+1}}{d'_{k+1}}\right) \end{aligned} \tag{A17}$$

Notice that because of our ordering of firms, $r_1 < r_k$. Thus the left-hand side of (A17) is greater than 1. As a result, we have $1 < r_1\left(\frac{d''_{k+1}}{d'_{k+1}}\right)$, thus $\frac{d'_{k+1}}{d''_{k+1}} < r_1$. Applying this result sequentially, we must have $\frac{d'_K}{d''_K} < r_1$. Since $\frac{d'_K}{d''_K} = r_K$, by construction, we have $r_K < r_1$. This contradicts our ordering of firms and thus clearly cannot hold. By contradiction, the vector of equilibrium shares and the associated vectors of wages and labor choices must be unique. This contradiction establishes the uniqueness result. (Q.E.D).

Second, we show that a unique equilibrium K^* exists. Suppose there exist 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:

$$\Pi^{K_1}\left(z^{(K_1)}\right) \geq 0 > \Pi^{K_1+1}\left(z^{(K_1+1)}\right) \quad \text{and} \quad \Pi^{K_2}\left(z^{(K_2)}\right) \geq 0 > \Pi^{K_2+1}\left(z^{(K_2+1)}\right) \tag{A18}$$

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

$$0 > \Pi^{K_1+1}\left(z^{(K_1+1)}\right) \geq \Pi^{K_2}\left(z^{(K_2)}\right) \geq 0. \tag{A19}$$

This condition clearly cannot hold. Therefore the equilibrium K^* is unique. From (A4), and given the set of firm productivities, K^* determines all firm-level variables in equilibrium. (Q.E.D).

A.4. Proposition 2

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

We first show that $K^{*'}(\tau^O) \geq 0$. To begin with, notice that holding the number of firms K^* fixed, the vector of equilibrium shares is the unique solution to the system of Eq. (A11) and, thus, does not change in response to change in aggregate conditions, i.e., change in Λ in Eq. (A4).

Recall from Eq. (20) that $\mathbf{P}'(\tau^O) \geq 0$, because lower output tariff increases competition in the product market and decreases the aggregate price. This leads to lower Λ. Plugging this condition into Eq. (A4), it is straightforward to observe that equilibrium wages decrease and that equilibrium profits decrease along with the wage conditioning on the same shares. Thus, $\Pi'(\tau^O,.) \geq 0$ for all z, holding the number of firms fixed. We now change K^* and show that $K^{*'}(\tau^O) \geq 0$ by contradiction.

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 $\Pi^{K_1^*,\tau_1^O}\left(z^{(K_1+1)}\right) < 0$ and $\Pi^{K_2^*,\tau_2^O}\left(z^{(K_1+1)}\right) \geq 0$. Noticing also that from the profit monotonicity condition, we must have $\Pi^{K_2^*}\left(z^{(K_1+1)}\right) \leq \Pi^{K_1^*}\left(z^{(K_1+1)}\right)$. Combining these inequalities, we have:

$$\Pi^{K_1^*,\tau_1^O}\left(z^{(K_1+1)}\right) < 0 \leq \Pi^{K_2^*,\tau_2^O}\left(z^{(K_1+1)}\right) \leq \Pi^{K_1^*,\tau_2^O}\left(z^{(K_1+1)}\right) \leq \Pi^{K_1^*,\tau_1^O}\left(z^{(K_1+1)}\right). \tag{A20}$$

Expressions in (A20) clearly cannot hold. Therefore, it must be true that as $\tau_1^O > \tau_2^O$, then $K_1^* \geq K_2^*$. (Q.E.D).

Second, we show that market shares and distortion increase for all incumbent firms as τ^O decreases. Consider a reduction in τ^O, and suppose that the reduction is large enough to induce exits of at least one firm $z^{(K*)}$. We will show that $s^{K^*}\left(z^{(k)}\right) \geq s^{K^*-1}\left(z^{(k)}\right)$ for all $k \leq K^* - 1$. It is cumbersome to show this result analytically using calculus. However, we could utilize the proof for uniqueness in section A.3.

Again, in the subsequent part of this section, the productivity ranking of firms will not matter for the proof; thus, I index firms by subscript k rather than productivity z. Let's the vector of equilibrium shares when $K = K^*$ be $(s'_1, \ldots, s'_{K^*-1}, s'_{K^*})$ and the vector of equilibrium shares when $K = K^* - 1$ be $(s''_1, \ldots, s''_{K^*-1})$. Here, $s'_{K^*} = s^{K^*}(z^{(K*)})$. We will show by contradiction that $s'_k \leq s''_k$ for all $1 \leq k \leq K^* - 1$. Suppose otherwise that $s'_\kappa > s''_\kappa$ for some $1 \leq \kappa \leq K^* - 1$.

For any $k = 1, \ldots, K^* - 1$, let $r_k = \left(\frac{m(s_k^{'})\tilde{z}_k}{m(s_k^{''})\tilde{z}_k}\right)^{\eta+1}$ and reshuffle firms by index k such that $r_k \leq r_l$ for any $k \leq l$.[69] Similar to the uniqueness proof, we must have $r_K < 1$ and thus $r_1 < 1$, since $m(.)$ is a decreasing function. For any k, denote:

$$\begin{aligned} d_k^{'} &\equiv \left(m\left(s_k^{'}\right)\tilde{z}_k\right)^{\eta+1} + \ldots + \left(m\left(s_{K^*-1}^{'}\right)\tilde{z}_{K^*-1}\right)^{\eta+1} + \left(m\left(s_{K^*}^{'}\right)\tilde{z}_{K^*}\right)^{\eta+1} \\ d_k^{''} &\equiv \left(m\left(s_k^{''}\right)\tilde{z}_k\right)^{\eta+1} + \ldots + \left(m\left(s_{K^*-1}^{''}\right)\tilde{z}_{K^*-1}\right)^{\eta+1} \end{aligned} \tag{A21}$$

Following similar steps as in the uniqueness proof, we can show that $\frac{d_k^{'}}{d_k^{''}} < r_1 \quad \forall \ 2 \leq k \leq K^* - 1$. When $k = K^* - 1$, we must have:

$$\begin{aligned} r_{K^*-1} = \frac{(m(s'_{K^*-1})\tilde{z}_{K^*-1})^{\eta+1}}{(m(s''_{K^*-1})\tilde{z}_{K^*-1})^{\eta+1}} &\leq \frac{(m(s'_{K^*-1})\tilde{z}_{K^*-1})^{\eta+1} + (m(s'_{K^*})\tilde{z}_{K^*})^{\eta+1}}{(m(s''_{K^*-1})\tilde{z}_{K^*-1})^{\eta+1}} \\ &= \frac{d'_{K^*-1}}{d''_{K^*-1}} < r_1 \end{aligned} \tag{A22}$$

Inequalities in (A22) clearly cannot hold due to our reshuffling. By contradiction, we must have $s_k^{'} \leq s_k^{''}$ for all $1 \leq k \leq K^* - 1$, i.e., labor market shares of incumbent firms increase as some firms exit the market due to lower tariff τ^O. From Eq. (14), since distortion is an increasing function of share, we also have the labor market distortion increase. These results conclude the proof for Proposition 2. (Q.E.D).

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 $\frac{(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)}{1-(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)}$, the adjusted relative factor shares between labor and intermediate input.

To see this, notice that a change in input tariff τ^I affects the competition in the labor market through a similar channel as output tariff τ^O; that is, they both affect the labor demand *MRPL*. Therefore, all the 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 Eq. (22), I can derive the modified *MRPL* of firm z as:

$$MRPL(z) = z^{\frac{\gamma-1}{\gamma}} L(z)^{\alpha\left(\frac{\gamma-1}{\gamma}\right)-1} M(z)^{(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)} \alpha\left(\frac{\gamma-1}{\gamma}\right) \mathbf{P}^{\frac{\gamma-1}{\gamma}} \mathbf{I}^{\frac{1}{\gamma}} \tag{A23}$$

From Eq. (A23), conditional on the same amount of labor $L(z)$, change in labor demand is determined by:

$$d \log\left(MRPL(z)\right) = (1-\alpha)\left(\frac{\gamma-1}{\gamma}\right) d \log\left(M(z)\right). \tag{A24}$$

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

$$d \log\left(M(z)\right) = -\frac{1}{1-(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)} d \log\left(1+\tau^I\right). \tag{A25}$$

Combine (A24) and (A25), the change in labor demand as a result of the change in input tariff is:

$$d \log(MRPL(z)) = -\frac{(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)}{1-(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)} d \log\left(1+\tau^I\right). \tag{A26}$$

Note that in the above equation, the magnified factor $\frac{(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)}{1-(1-\alpha)\left(\frac{\gamma-1}{\gamma}\right)} \to \frac{1-\alpha}{\alpha}$ as $\gamma \to \infty$ i.e. perfect competition in product market. Eq. (A26) concludes the proof for Proposition 3. (Q.E.D).

[69] Here, $\tilde{z}_k = z_k^{\frac{\gamma-1}{\gamma+\theta}}$

Appendix B. Production Function Estimation

This appendix provides supplementary notes for the production function estimation procedure in Section 3. In particular, I provide detailed derivations of a firm's profit maximization problem, timing assumptions, and 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 follows:

$$\max_{M_t} \mathbb{E}\left[F(k_t, l_t, m_t) * e^{(\omega_t+\varepsilon_t)}|\mathbb{I}_t\right] - p_{M_t} M_t, \tag{B1}$$

where $F(.)$ and M_t are the exponential counterparts of $f(.)$ and m_t in Eq. (26) respectively. p_{M_t} is the price of material, taken as given by the firm. Taking FOC of this problem yields:

$$\frac{\partial}{\partial M_t} F(k_t, l_t, m_t) e^{\omega_t} E\left[e^{\varepsilon_t}\right] - p_{M_t} = 0. \tag{B2}$$

Taking the log version of the above equation, I obtain the following:

$$\begin{aligned} log\left(s_t^M\right) \equiv log\frac{p_{M_t} M_t}{R_t} &= log E\left[e^{\varepsilon_t}\right] + log\frac{\partial}{\partial m_t} f(k_t, l_t, m_t) - \varepsilon_t \\ &= log\frac{\partial}{\partial m_t} f(k_t, l_t, m_t) - \varepsilon_t. \end{aligned} \tag{B3}$$

The second equality of (B3) (also Eq. (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 ε_t (see also in Gandhi et al. (2020)). In the Chinese firm-level data, the estimated $\hat{\varepsilon}_t$ exhibits little asymmetry and requires minimum correction, i.e., $E\left[e^{\hat{\varepsilon}_t}\right] \approx 1$ for most industries.

In what follows, $\mathbf{v}_t$ 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 are as follows:

- At the end of period $(t-1)$, the firm chooses $(k_t, l_t, \mathbf{v}_t)$ and whether to exit at t.
- At the beginning of period t, η_t (and hence ω_t) realizes. The firm observes their productivity for period t.
- The firm optimally chooses m_t, after which ε_t realizes and completely determines r_t.
- At the end of t, the firm chooses $(k_{t+1}, l_{t+1}, \mathbf{v}_{t+1})$ and whether to exit at $t+1$, repeating the same process.

The moment conditions for the second GMM stage are:

$$E\left[\eta_t \otimes \left(\begin{bmatrix} 1 \\ \Psi_{t-1} \\ C_t(.) \\ C_{t-1}(.) \end{bmatrix}\right)\right] = 0 \tag{B4}$$

Appendix C. Data Construction and Filtering

China's Annual Survey of Industrial Enterprises (ASIE) data records firms' balance sheet 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. The matching code follows the published code in Brandt et al. (2014).

After matching, my cleaning procedure is performed as follows, in sequential steps:

- Step 1: Drop all firms with missing values of key variables: output (revenue), real capital stocks, employment, materials, wage bill, and export status.
- Step 2: Drop all firms with values of key variables outside of range $0.5th$ and $99.5th$ percentiles. These variables include output (revenue), real capital stocks, employment, materials, wage bill, average wage, labor share, and input share.
- Step 3: Drop all firms with labor share and input share outside of range $[0,1]$.
- Step 4: Drop all firms with output (revenue) below 5 million Renminbi (RMB) and employment below 8 workers to keep consistent size thresholds.
- Step 5: Drop all firms that switch 2-digit industries. This ensures a consistent production function estimation at the 2-digit industry level and correct tariff exposures for each firm.

My cleaning procedures are similar to standard practices in the literature that uses ASIE data; see, for example, Brandt et al. (2014) and Brandt et al. (2017).

Appendix D. Linking Nonparametric Distortion Measure to Oligopsony

This appendix explores the relationship between variation in the nonparametric measure obtained in Section 3 and the firm's local labor market share to link the distortion measure to oligopsonistic competition.[70] More specifically, motivated by Eq. (14) in the theory, I run the following regression:

$$\tilde{\chi}_{ijlt} = \lambda s_{ijlt} + \gamma_i + \gamma_{cic2,t} + \gamma_{lt} + \varepsilon_{ijlt}. \tag{D1}$$

Here, $\tilde{\chi}_{ijlt}$ is the nonparametric distortion measure of firm i, in (4-digit) industry j, location l, and year t. s_{ijlt} is firm's local labor market (wage-bill) share, computed as $s_{ijlt} = \frac{w_{ijlt}L_{ijlt}}{\sum_k w_{kjlt}L_{kjlt}}$. γ_i controls for firm fixed effects. $\gamma_{cic2,t}$ controls for 2-digit industry-by-year fixed effects. γ_{lt} controls for location-by-year fixed effects. If there is oligopsony, we would expect the estimated parameter λ to be positive and significant.[71] There are two caveats in estimating Eq. (D1). First, since a firm's wage bill simultaneously appears on the left-hand side (in the denominator of $\tilde{\chi}_{ijlt} = \frac{MRPL_{ijlt}}{w_{ijlt}}$) and on the right-hand side (in the numerator of $s_{ijlt} = \frac{w_{ijlt}L_{ijlt}}{\sum_k w_{kjlt}L_{kjlt}}$), there is a negative mechanical correlation between these two terms, likely due to measurement errors in wage bill. To circumvent the issue with measurement errors, I follow Brooks et al. (2021)'s approach in instrumenting for the wage-bill share in Eq. (D1). A second but also important caveat in Eq. (D1) is the presence of strategic interactions between firms that likely weaken the correlation between market share and the reduced-form measure of distortion. This is indeed one of the key points made by Berger et al. (2022). Resolving the second caveat requires that the instrument should be at the market level rather than at the firm level.

I instrument for firm's local labor market share by local labor market HHIs and local product market HHIs. Specifically,

$$HHI^{w}_{jlt} = \sum \left[\frac{w_{ijlt}L_{ijlt}}{\sum\limits_k w_{kjlt}L_{kjlt}} \right]^2 \quad \text{and} \quad HHI^{R}_{jlt} = \sum \left[\frac{R_{ijlt}}{\sum\limits_k R_{kjlt}} \right]^2,$$

where $(w_{ijlt}L_{ijlt})$ is firm i's wage bill and R_{ijlt} is firm i's revenue. The HHIs are the conventional Herfindahlâ€"Hirschman indices, calculated at the local market (jl) level. Intuitively, these HHIs summarize the overall changes in oligopsony within a local labor market meanwhile alleviating issues created by measurement errors or strategic interactions between individual firms. The coefficient λ is thus identified by comparing average firms across markets (jl) with different levels of competition rather than comparing firms within the same market. My preferred instruments to estimate λ are different from Brooks et al. (2021); however, I also follow Brooks et al. (2021) in using the firm's local revenue share as an instrument for the firm's local labor market share to eliminate measurement errors and find similar results to theirs in terms of magnitude. The results for Eq. (D1) are shown in Table D1. Columns (1)–(3) show the results for local labor market share as defined in the paper (4-digit industry × prefecture) with three different instruments. The estimated parameters $\hat{\lambda}$ across all columns indicate that an increase in labor market share due to an increase in concentration is positively associated with an increase in labor market distortion. In particular, based on my preferred estimates in columns (1)–(2), the estimated $\hat{\lambda}$ ranges from 0.06 to 0.08. These are not small numbers. They indicate that moving from 1 firm (share = 100%) to 2 firms (average share = 50%) increases wage pass-through by 3–4%. I also estimate much larger coefficients when using the firm's local revenue share as the instrument in column (3), and they are similar in order of magnitude to Brooks et al. (2021). In columns (4)–(6), I implement a robustness check by defining the local labor market at the 2-digit industry × prefecture level. I find similar results though the magnitude of $\hat{\lambda}$ is larger when the boundary of local labor markets is extended, similar to findings in Brooks et al. (2021)).[72] Here, a more recent structural estimate by Felix (2021) might provide a useful benchmark. Felix (2021) estimates parameters θ and η separately for Brazil's labor market, implying an estimated $\hat{\lambda}$ of 0.272. Although local labor markets are defined somewhat differently, Felix (2021)'s results and the results here in columns (4)–(5) are reassuringly similar in terms of magnitude.[73] Columns (7)–(9) show the result of regressing the nonparametric measure ($\tilde{\chi}_{ijlt}$) on the parametric one ($\tilde{\chi}^e(s_{ijlt})$) obtained in Section 4, using the same instrument set. The measure $\tilde{\chi}^e(s_{ijlt})$ is a nonlinear but monotonic transformation of s_{ijlt}, as shown in Fig. 4 of the paper. The estimated coefficients in columns (7)–(8), ranging from 0.60 to 0.83, imply a high correlation between the two measures, driven by the changes in local HHIs (the changes in local market competition). Overall, the results across all columns in Table D1 strongly support the narrative that both the nonparametric and parametric measures were able to capture variation in distortion due to oligopsony.

[70] I am extremely grateful to an anonymous referee and editor for pointing me to perform this analysis.

[71] A consistently estimated $\hat{\lambda}$ would be equal to $\widehat{(\frac{1}{\theta} - \frac{1}{\eta})}$.

[72] This is generally a matter of technicality. Larger markets correspond to smaller market shares. As a result, the exact same correlation pattern in the data would exhibit a larger coefficient.

[73] Felix (2021) defines local labor markets as micro-regions in Brazil without the industry dimension. This definition is comparable to my defined local labor markets if labor mobility is costly across industries, which is typically the case in developing countries (see, for example, Artuc et al. (2015)).

Table D1
Association between Nonparametric Distortion Measure and Labor Market Share (Oligopsony).

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		$\tilde{\chi}_{ijlt}$			$\tilde{\chi}_{ijlt}$			$\tilde{\chi}_{ijlt}$	
Instrument	HHI^{w}_{jlt}	HHI^{R}_{jlt}	s^{R}_{ijlt}	HHI^{w}_{jlt}	HHI^{R}_{jlt}	s^{R}_{ijlt}	HHI^{w}_{jlt}	HHI^{R}_{jlt}	s^{R}_{ijlt}
Endogenous Variable									
s_{ijlt}	0.077***	0.061***	0.946***						
	(0.014)	(0.014)	(0.012)						
s_{ijlt} (2-digit industry)				0.285***	0.144***	3.015***			
				(0.048)	(0.049)	(0.032)			
$\tilde{\chi}^{e}(s_{ijlt})$							0.597***	0.831***	2.439***
							(0.021)	(0.033)	(0.026)
Observations	1,235,801	1,235,801	1,235,801	1,235,801	1,235,801	1,235,801	1,074,093	1,074,093	1,074,093
Fixed Effects									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Firm-level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (D1) with three different instruments: local labor market HHI^{w}_{jlt}, local revenue HHI^{R}_{jlt}, and local revenue share of firms s^{R}_{ijlt} ($s^{R}_{ijlt}=\frac{R_{ijlt}}{\sum_k R_{kjlt}}$). Endogenous variables are local labor market share s_{ijlt} at 4-digit industry × prefecture level, local labor market share at 2-digit industry × prefecture level, and parametric distortion measure in Section 4, respectively. Standard errors are clustered at the firm level. First-stage results indicate strong instruments for all three. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix E. Using an Alternative Distortion Measure in Bau and Matray (2020)

In this appendix, I describe an alternative measure of labor market distortion used in Bau and Matray (2020) that does not rely on production function estimation techniques and present the regression results in Table 5 using this alternative measure.

In Bau and Matray (2020), the revenue production function within each 4-digit industry is assumed to be Cobb-Douglas. Under this assumption, the within-industry residual variation in labor share is informative about the within-industry variation in labor market distortion. More specifically, this assumption translates to holding the labor elasticity of revenue constant within each industry instead of allowing this elasticity to vary across firms. Thus, labor market distortion of firm i in industry j and year t can be written as:

$$\tilde{\chi}^{alt}_{ijt}=\frac{MRPL_{ijt}}{w_{ijt}}=\theta^{L}_{j}\frac{R_{ijt}}{w_{ijt}L_{ijt}}=\theta^{L}_{j}\frac{1}{laborshare_{ijt}}. \tag{E1}$$

Notice that in Eq. (E1), θ^{L}_{j} is the same for all firms within an industry. Taking the logs on both sides. We have:

$$log\left(\frac{1}{laborshare_{ijt}}\right)=-log\left(\theta^{L}_{j}\right)+log\left(\tilde{\chi}^{alt}_{ijt}\right). \tag{E2}$$

From the result in Eq. (E2), I estimate $log\left(\tilde{\chi}^{alt}_{ijt}\right)$ by regressing the log of inverse labor share on a set 4-digit industry fixed effects. This residual variation of labor share captures the within-industry variation in labor market distortion.

With this alternative measure in hand, I re-examine my main results in Table 5 and report them in Table E1. As shown in this table, the effects of tariffs on this measure of labor market distortion are strongly consistent with the main results in Table 5. However, the magnitudes of the effects here are larger for both output and input tariff reduction, highlighting the importance of taking into account production function heterogeneity and the effects of trade on it.

In addition to what is used in Bau and Matray (2020), I also relax the Cobb-Douglas revenue production function assumption, which is effectively equivalent to a Cobb-Douglas physical production function and constant markup, by removing from the residual distortion the gross-profit margin (I use the ratio $\frac{sales}{costs}$ to approximate markup). I find similarly robust results in this case as well and report those results in Table E2.[74]

[74] In particular, the gross profit margin is calculated as $\frac{sales}{costs}=\frac{Revenue}{UserCostofCapital+WageBill+MaterialCosts}$, wherein I use 0.12 as the rental rate of capital, adopting from Brooks et al. (2021).

Table E1
Impact of Tariff Changes on the Labor Market Distortion using Alternative Measure in Bau and Matray (2020).

Dependent Variable	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$
	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariffs ($\tau_{j,t-1}^{O}$)	−0.045		−0.085	−0.126
	(0.088)		(0.089)	(0.091)
Input Tariffs ($\tau_{j,t-1}^{I}$)		0.761**	0.867**	1.110***
		(0.358)	(0.348)	(0.369)
Observations	1,260,891	1,260,891	1,260,891	1,260,891
R-squared	0.736	0.736	0.736	.
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (39) using the alternative measure in Bau and Matray (2020). 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. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table E2
Impact of Tariff Changes on the Labor Market Distortion using Alternative Measure in Bau and Matray (2020) (Purged out Gross-Profit Margin).

Dependent Variable	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$	$log\left(\tilde{\chi}_{ijlt}^{alt}\right)$
	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)
Output Tariffs ($\tau_{j,t-1}^{O}$)	−0.045		−0.082	−0.116
	(0.087)		(0.087)	(0.089)
Input Tariffs ($\tau_{j,t-1}^{I}$)		0.697*	0.798**	1.010***
		(0.358)	(0.344)	(0.365)
Observations	1,260,891	1,260,891	1,260,891	1,260,891
R-squared	0.731	0.731	0.731	.
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (39) using the alternative measure in Bau and Matray (2020) after purging out the gross-profit margin (as a proxy for markup). 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. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix F. Markup

This appendix exploits production function estimation in Section 3.1 to measure firm-level markup. Here, due to the lack of firm-level price information, I follow Flynn et al. (2019) in imposing the constant return-to-scale (CRS) physical production function assumption to infer the markup and regress this measure on China's trade policy changes as in Eq. (39). Following Flynn et al. (2019) with CRS assumption, markup is calculated as: $markup = \frac{1}{\frac{\partial r}{\partial k}+\frac{\partial r}{\partial l}+\frac{\partial r}{\partial m}}$. The markup regression results are shown in Table F1.

Across columns (1)–(6), a robust result is that lowering input tariffs increases firm-level markup. This result is statistically significant and qualitatively consistent with previous findings in the literature (De Loecker et al. (2016), Brandt et al. (2017)). On the other hand, lowering output tariffs has almost no substantive economic impact on firm-level markup. Comparing the magnitude of the effect on markup versus the effect on labor market distortion in Table 5, the effect of trade policy on markup is an order of magnitude smaller. Importantly, the effect of tariff changes on markup works in the opposite direction of the effect on labor market distortion. That is, China's trade policy reform has led to a net increase in firm-level markup, meanwhile also leading to a net decrease in firm-level labor market distortion. Therefore, the markup regression results rule out the possibility that the intensive margin is the channel through which China's trade policy affects labor market distortion.[75]

Table F1
Impact of Tariff Changes on Markup.

Dependent Variable	Markup (in Log)					
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Output Tariffs ($\tau^{O}_{j,t-1}$)	−0.006**	−0.009***			−0.005	−0.007**
	(0.003)	(0.003)			(0.003)	(0.003)
Input Tariffs ($\tau^{I}_{j,t-1}$)			−0.041***	−0.046**	−0.035**	−0.037*
			(0.015)	(0.019)	(0.017)	(0.020)
Observations	1,235,801	1,235,801	1,235,801	1,235,801	1,235,801	1,235,801
R-squared	0.873	.	0.873	.	0.873	.
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Two-way						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (39) with the dependent variable as the log of markup. 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. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

[75] It is important to emphasize that constant return to scale (CRS) is clearly a strong assumption and the markup regression results here should be interpreted with care. Since the markup measure relies on the assumption that physical production technology is constant return to scale (CRS), the regression results could be biased if production return-to-scale responds to tariff shocks. For instance, firms could expand/contract production scale and alter the long-run marginal cost in response to tariff changes.

Appendix G. Heterogeneous Effects

Table G1
Heterogeneous Effects by Industry Characteristics (IV Estimates).

Dependent Variable	$log\left(\tilde{\chi}_{ijlt}\right)$				$log\left(\tilde{\chi}^e(s_{ijlt})\right)$			
	Export	SOE	Female	Skill	Export	SOE	Female	Skill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Output Tariffs ($\tau^O_{j,t-1}$)	−0.108	−0.085	−0.135	0.135	−0.069**	−0.155***	0.001	−0.373***
	(0.074)	(0.105)	(0.194)	(0.174)	(0.034)	(0.044)	(0.079)	(0.066)
Input Tariffs ($\tau^I_{j,t-1}$)	−0.230	0.639	1.100	−0.900	−0.184	0.904***	−1.539***	1.775***
	(0.542)	(0.605)	(0.970)	(0.960)	(0.247)	(0.331)	(0.448)	(0.442)
Export Share $\times\tau^O_{j,t-1}$	0.439				0.179			
	(0.267)				(0.142)			
Export Share $\times\tau^I_{j,t-1}$	4.579*				2.660**			
	(2.440)				(1.283)			
SOE Share $\times\tau^O_{j,t-1}$		0.360				0.859***		
		(0.563)				(0.287)		
SOE Share $\times\tau^I_{j,t-1}$		−0.386				−3.697**		
		(3.046)				(1.580)		
Female Share $\times\tau^O_{j,t-1}$			0.232				−0.062	
			(0.411)				(0.168)	
Female Share $\times\tau^I_{j,t-1}$			−1.005				3.660***	
			(1.815)				(0.819)	
Skill Ratio $\times\tau^O_{j,t-1}$				−0.243				0.493***
				(0.235)				(0.101)
Skill Ratio $\times\tau^I_{j,t-1}$				2.137				−2.158***
				(1.350)				(0.577)
Observations	1,235,801	1,235,801	1,235,801	1,235,801	1,074,093	1,074,093	1,074,093	1,074,093
Fixed Effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Two-way								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the IV results of regression EQ. (39) with heterogeneous effects. 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. Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix H. Robustness to Local Labor Supply Shocks

Table H1
Robustness to Local Labor Supply Shocks.

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Dependent Variable	$\left(\tilde{\chi}_{ijlt}\right)$	$\left(\tilde{\chi}_{ijlt}\right)$	$\left(\tilde{\chi}^{e}\left(s_{ijlt}\right)\right)$	$\left(\tilde{\chi}^{e}\left(s_{ijlt}\right)\right)$
Panel A: Including (2-digit) Industry × Location × Year Fixed Effects				
Output Tariffs $\left(\tau^{O}_{j,t-1}\right)$	−0.016	−0.017	−0.028	−0.034
	(0.061)	(0.056)	(0.022)	(0.024)
Input Tariffs $\left(\tau^{I}_{j,t-1}\right)$	0.502*	0.554*	0.355**	0.441***
	(0.277)	(0.305)	(0.150)	(0.168)
Observations	1,235,801	1,235,801	1,074,093	1,074,093
R-squared	0.775	.	0.709	.
Panel B: Dropping Firms Ever Had SOE Ownership				
Output Tariffs $\left(\tau^{O}_{j,t-1}\right)$	−0.015	−0.018	−0.050**	−0.055**
	(0.065)	(0.062)	(0.024)	(0.026)
Input Tariffs $\left(\tau^{I}_{j,t-1}\right)$	0.590**	0.615*	0.380**	0.433**
	(0.285)	(0.319)	(0.149)	(0.169)
Observations	1,098,546	1,098,546	979,434	979,434
R-squared	0.770	.	0.707	.
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Industry-Location-Year (2-digit)	Yes	Yes	Yes	Yes
Clustered Two-way				
Firm	Yes	Yes	Yes	Yes
Industry-by-Year (2-digit)	Yes	Yes	Yes	Yes

Note: The table reports the results of regression Eq. (39), similar to results in Table 5 but including 2-digit industry × location × year fixed effects (Panel A) and dropping firms that have ever had SOE ownership (Panel B). Standard errors in parentheses are clustered two-way at the firm and industry-by-year levels ($p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix I. Distribution and Correlation Patterns of Parametric Measure

The measure of distortion using the parametric approach has quite limited variation compared to the measure using the production function approach. However, to cross-validate between the two measures, Fig. I1-I2 reproduce Fig. 2-3, respectively. The evolution and correlation patterns are very similar between the two measures. Specifically, in the right panel of Fig. I1, the distribution of this endogenous distortion is becoming less dispersed over time and is associated with reductions in both the mean and median. In terms of industry characteristics in Fig. I2, industries that are more export-oriented and employ more female workers are also associated with lower levels of labor market distortion. On the other hand, industries that have higher shares of state ownership and high-skill workers are associated with greater distortion. The differences between the two measures are the *absolute* level of distortion and its across-firm dispersion, which is illustrated in the right panel of Fig. I1. 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. This resonates with the results in Gaubert and Itskhoki (2021), in which they also find limited variation in product market distortion due to market shares.

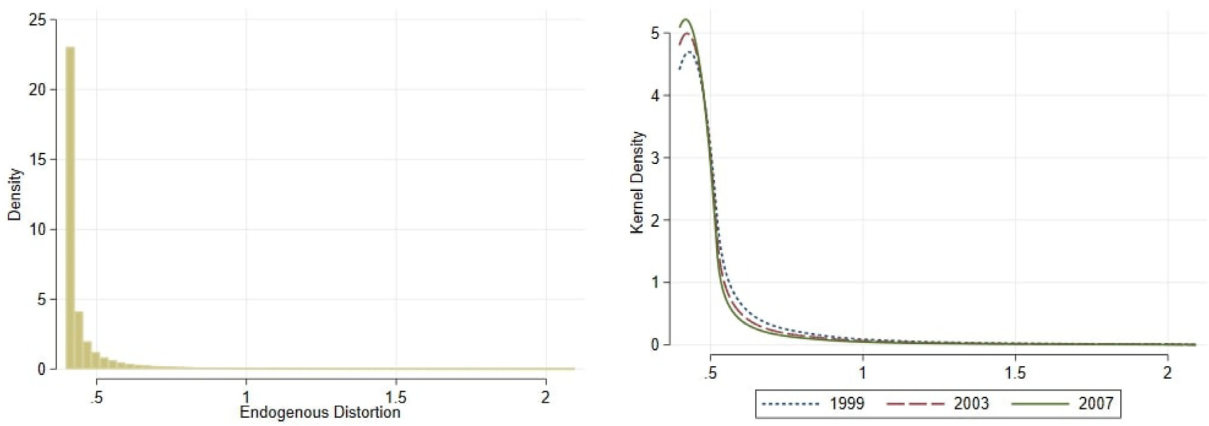

Fig. I1. Distribution of the Endogenous Distortion ($log\left(\tilde{\chi}^{e}\left(s_{ijlt}\right)\right)$).
Note: The figure is a counterpart of Fig. 2, but for the endogenous distortion $\left(\tilde{\chi}^{e}\left(s_{ijlt}\right)\right)$ rather than the overall distortion $\left(\tilde{\chi}_{i}\right)$. 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, and 2007.

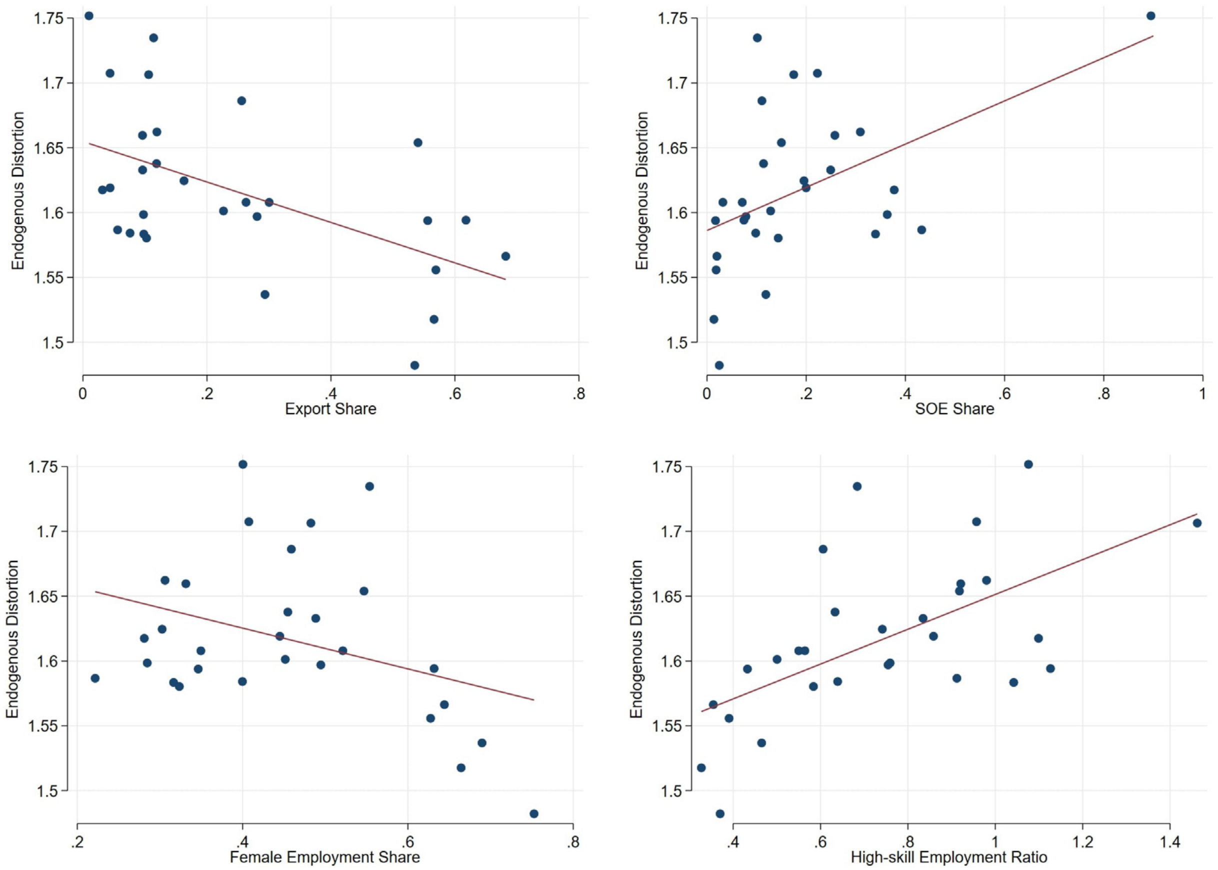

Fig. I2. Endogenous Distortion ($\tilde{\chi}^e(s_{ijlt})$) and Industry Characteristics (in year 2004).

Note: The figure is a counterpart of Fig. 3, but for the endogenous distortion ($\tilde{\chi}^e(s_{ijlt})$) rather than the overall distortion ($\tilde{\chi}_i$). It shows the correlations between the measured endogenous distortion ($\tilde{\chi}^e(s_{ijlt})$) 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 from 2004 because this is the only year that the employment composition information is available.

Appendix J. Additional Figures and Tables

Table J1

Aggregate Summary Statistics of the Chinese Firm-level Data.

Year	No. of Firms	VA	Sales	Output	Employment	Export	Fixed Assets (Net)
1998	165,118	1.94	6.54	6.77	56.44	1.08	4.41
1999	162,033	2.16	7.06	7.27	58.05	1.15	4.73
2000	162,882	2.54	8.37	8.57	53.68	1.46	5.18
2001	171,256	2.83	9.19	9.54	54.41	1.62	5.54
2002	181,557	3.30	10.86	11.08	55.21	2.01	5.95
2003	196,220	4.20	13.95	14.23	57.48	2.69	6.61
2004	279,092	6.62	19.78	20.17	66.22	4.05	7.97
2005	271,835	7.22	24.69	25.16	69.31	4.77	8.95
2006	301,961	9.11	31.08	31.66	73.49	6.05	10.58
2007	336,768	11.70	39.76	40.51	78.75	7.34	12.34

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 of Renminbi (RMB).

Table J2
Revenue Elasticities and Labor Market Distortion by Industry (ACF-Translog).

Industry	Capital	Labor	Material	$\tilde{\chi}_i$ (**Mean**)
13. Food Processing	0.19	0.19	.	6.94
14. Food Production	0.21	0.19	.	3.58
15. Beverage	0.21	0.06	.	1.23
16. Tobacco	0.39	0.33	.	3.10
17. Textile	0.22	0.21	.	3.50
18. Garments	0.14	0.35	.	3.16
19. Leather	0.17	0.26	.	2.86
20. Timber	0.25	0.25	.	4.68
21. Furniture	0.14	0.34	.	4.73
22. Paper-making	0.23	0.21	.	4.24
23. Printing	0.19	0.08	.	1.03
24. Cultural	0.16	0.26	.	2.80
25. Petroleum Processing	0.25	0.19	.	4.75
26. Raw Chemical	0.23	0.13	.	2.71
27. Medical	0.27	0.15	.	2.60
28. Chemical Fibre	0.33	0.19	.	5.22
29. Rubber	0.19	0.10	.	1.55
30. Plastic	0.20	0.22	.	3.81
31. Nonmetal Products	0.19	0.04	.	0.47
32. Processing of Ferrous	0.30	0.26	.	7.13
33. Processing of Nonferrous	0.22	0.20	.	5.79
34. Metal Products	0.21	0.19	.	2.93
35. Ordinary Machinery	0.19	0.12	.	1.72
36. Special Equipment	0.16	0.14	.	1.87
37. Transport Equipment	0.25	0.27	.	4.32
39. Electric Machinery	0.25	0.23	.	4.05
40. Electronic and Telecom	0.21	0.35	.	4.83
41. Measuring Instruments	0.13	0.13	.	1.28
42. Art Work	0.15	0.17	.	1.73
All Industry	0.21	0.20	.	3.40

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 et al. (2015) (ACF). All statistics are the mean of respective distributions. The ACF method used here identifies a structural value-added production function and assumes that the (gross-output) production function is of Leontief form, i.e., perfect complementarity between material and other factors. The table trims observations above and below the 1^{st} and 99^{th} percentiles.

Table J3
China's Tariffs Evolution from 1998 to 2007.

Year	Output Tariff (τ^O)		Input Tariff (τ^I)	
	Average	Std. Deviation	Average	Std. Deviation
	(1)	(2)	(3)	(4)
1998	0.16	0.09	0.11	0.03
1999	0.16	0.09	0.11	0.03
2000	0.16	0.09	0.11	0.03
2001 (WTO)	0.15	0.08	0.10	0.03
2002	0.12	0.07	0.08	0.03
2003	0.11	0.07	0.07	0.02
2004	0.10	0.06	0.06	0.02
2005	0.09	0.06	0.06	0.02
2006	0.09	0.06	0.06	0.02
2007	0.09	0.06	0.06	0.02
Total	0.12	0.08	0.08	0.03

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.

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