The impact of trade liberalization on firms' product and labor market power*

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Abstract

This paper examines the impact of trade liberalization on firms' product and labor market power. We estimate the prevalence and intensity of firm-level price-cost markups and either wage markups or wage markdowns. We take the dependence between these model-consistent measures of product and labor market power explicitly into account. To identify the effect of trade shocks on product and labor market power, we exploit China's reductions in input and output tariffs upon its accession to the World Trade Organization. We find that trade liberalization has not switched firms away from exercising product and labor market power. Reducing tariffs on intermediate inputs has increased a firm's price-cost markup but decreased the degree of wage-setting power that it possesses, conditional on exercising product/labor market power. Finally, we find heterogeneous trade liberalization effects on the intensity of firms' product and labor market power, giving insights into the true consequences of trade shocks.

Keywords: Price-cost markups, wage markups, wage markdowns, trade liberalization, tariffs.

JEL classification: F14, F16, L11, P31.

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1. Introduction

Since the onset of economic reform in 1978, China's transformation into a market-driven economy has led to rapid economic growth. The role of market forces in allocating resources has been accelerated by the country's entry to the World Trade Organization at the end of 2001.[1]

Despite incentive mechanism and allocation system reforms, there still exist considerable interfirm dispersion of marginal factor returns.[2] Viewed through the lens of a static standard model of production and demand, such disparities suggest the existence of distortions to the functioning of markets. Notwithstanding overwhelming evidence on factor market distortions in China[3], no empirical study has so far estimated the impact of WTO entry on price distortions in product as well as labor markets, which is the main purpose of this study.[4]

We contribute to the empirical international trade literature by establishing the effect of trade liberalization on firms' product and labor market power using an actual liberalization period.[5] Such investigation is well justified for several reasons. First, recent theoretical heterogeneous-firms approaches to trade and wage inequality all draw on imperfect labor markets and consider rent sharing to be the key mechanism through which trade-induced variation in rents is transmitted to variation in wages. Second, disentangling the impact of trade liberalization on product versus labor market power matters a lot for policy concerned with allocative efficiency, (wage and consumption) inequality, welfare losses, and the falling labor share in national income. As such, our analysis sheds light on whether either market power on the supply side of labor or market power on the demand side of labor is predominantly responsible for distorting factor prices and whether the balance of power has shifted after WTO entry.

We generalize the model of De Loecker and Warzynski (2012) for obtaining firm-level price-cost markups which assumes that firms minimize costs with respect to labor and

[1] Maddison (2007), Branstetter and Lardy (2008), and Zhu (2012).

[2] Brandt and Zhu (2010) and Kamal and Lovely (2012).

[3] See World Bank and the Development Research Center of the State Council, P.R. China (2013) for references. Brandt *et al.* (2013) document that factor market distortions have increased significantly since 1997, reducing aggregate non-agricultural total factor productivity growth by half a percent a year.

[4] The effect of WTO membership on the degree of liberalization, firm performance (productivity and price-cost markups) and welfare gains has been extensively analyzed (see e.g. Chen and Ravallion, 2004; Lardy, 2004; Brandt *et al.*, 2012; Di Giovanni *et al.*, 2014; Brandt *et al.*, 2017).

[5] Trade economists have a long tradition of investigating the impact of globalization on firms' price-cost markups and have provided evidence on the procompetitive effect using actual trade liberalization episodes (see Tybout, 2008; De Loecker and Goldberg, 2014; De Loecker and Van Biesebroeck, 2018 for surveys).

materials. Such standard cost-minimization assumption rules out that firms exercise wage-setting power. We relax this assumption and nest two polar models of wage formation in imperfect labor markets in the seminal productivity model of Hall (1988) with price-setting firms. These imperfectly competitive labor market models are tied to two polar sources of labor market imperfections which give rise to wage-employment contracts off the firm's labor demand curve. Labor market imperfections may either stem from workers' monopoly power forcing employers to pay a wage markup, or from firms' monopsony power enabling them to set a wage markdown. As such, we consider two pricing rules in the product market (price-marginal cost and price-markup pricing) and three pricing rules in the labor market (wage-markdown, wage-marginal product and wage-markup pricing). Our model takes the dependence between pricing rules in the product and labor markets explicitly into account.

We estimate the prevalence and intensity of Chinese firms' market power using a panel of 57,577 manufacturing firms located in the three most important economic regions during the period 1999–2006, constructed from annual surveys conducted by the National Bureau of Statistics (NBS).

We then examine whether China's WTO membership has affected the product and labor market power of Chinese firms. As such, our application can be considered as a generalization of Brandt *et al.* (2017) who examine the impact of trade liberalization in China on the magnitude of price-cost markups (and productivity) of Chinese firms. To identify the effect of trade shocks on product and labor market power, we exploit China's reductions in input and output tariffs upon its WTO accession at the end of 2001, following Lu and Yu (2015) and Brandt *et al.* (2017). Intuitively, falling input tariffs might increase technical efficiency through access to lower-cost and superior intermediate products while output tariff cuts directly decrease domestic output prices and might indirectly decrease X-inefficiencies through reducing managerial slack and changing organizational structure.

Several novel findings emerge. First, we find that trade liberalization has not affected the prevalence of price-cost markups and wage markups/wage markdowns. More specifically, tariff reductions have not switched firms away from exercising product and labor market power.

Second, trade liberalization through tariff cuts on intermediate inputs has increased a firm's price-cost markup but decreased the degree of wage-setting power that it possesses, conditional on exercising product/labor market power respectively. The positive effect of input tariff cuts on the magnitude of price-cost markups confirms the finding of Brandt *et al.* (2017). The narrowing effect of input tariff cuts on wage markdowns (hence, the negative effect on firms' wage-setting power) is largely driven by state-owned enterprises.

Third, modeling the dependence between pricing rules in product and labor markets allows us to reveal heterogeneous trade liberalization effects on the intensity of firms' product and labor market power. We find that the positive impact of input tariffs cuts on firms' product market power (price-cost markups) is most pronounced for firms that exercise labor market power (set wage markdowns). Likewise, the negative impact of input tariffs cuts on firms' labor market power (narrowing impact on wage markdowns) is most pronounced for firms that exercise product market power (set price-cost markups).

The outline of the article is as follows. Section 2 presents the main ingredients of the theoretical structural productivity model with imperfect product and labor markets. Section 3 discusses the econometric model. Section 4 presents the classification and testing procedures to identify a firm's pricing rules in product and labor markets at any point in time. Section 5 presents the Chinese firm panel data. Section 6 reports the outcome of the testing procedure. Sections 7 documents the impact of trade liberalization on switching the prevalence of firms' product and labor market power. Section 8 presents the impact of trade liberalization on the intensity of firms' product and labor market power. Section 9 concludes.

2. Theoretical structural model with imperfect product and labor markets

To model a firm's product and labor market power, we follow Dobbelaere and Mairesse (2013) and nest two polar models of wage formation in imperfect labor markets in the seminal productivity model of Hall (1988) with imperfect product markets.

Each firm at any point in time produces output using labor, intermediate input and capital. We assume that all producers that are active in the market are maximizing short-run profits and take the price of intermediate inputs as given. [6] Each firm must choose the optimal quantity of output and the optimal demand for intermediate input and labor. In terms of the firm's input choices, we assume that intermediate input and labor are free of adjustment

[6]This assumption might be perceived as being restrictive, given recent evidence on the importance of imperfect competition in intermediate goods markets. Morlacco (2019) extends our model to account for imperfect competition in all variable input markets and uses full company accounts and exhaustive records of export and import flows of French firms. Kikkawa *et al.* (2019) rely on a model of oligopolistic competition in firm-to-firm trade and use business-to-business transactions of the universe of Belgian firms. We defend our restrictive assumption on two grounds. The first is a data reason. In line with Morlacco (2019), we could easily model imperfections in intermediate input markets as additional unit costs that create wedges between marginal costs and marginal products. However, data constraints preclude us from considering this choice. The second reason is that we prefer to focus our empirical analysis on the impact of trade shocks on firms' product and labor market power, abstaining from non-competitive buyer behavior in the market of intermediate inputs.

costs and thus choice variables in the short run whereas capital is predetermined and thus no choice variable in the short run.

The first-order condition for output yields the firm's price-cost markup $\mu_{it} = \frac{P_{it}}{(C_Q)_{it}}$, with P_{it} the output price and $(C_Q)_{it}$ the marginal cost of production.

The first-order condition for intermediate input is given by setting the marginal revenue product of intermediate input equal to the price of intermediate input: $(Q_M)_{it} = \mu_{it}\frac{J_{it}}{P_{it}}$. Using this first-order condition and the first-order condition for output, we obtain an expression for firm i's price-cost markup μ_{it}:

$$\mu_{it} = \frac{(\varepsilon^Q_M)_{it}}{\alpha^M_{it}}$$

with $(\varepsilon^Q_M)_{it}$ the output elasticity with respect to intermediate input and $\alpha^M_{it} = \frac{J_{it}M_{it}}{P_{it}Q_{it}}$ the share of intermediate input expenditure in total revenue. The value of μ_{it} determines the firm's type of competition prevailing in the product market or its product market setting (denoted PMS). The product market setting is defined to be perfectly competitive if the firm engages in marginal cost pricing (PMC) and, hence, has no product market power. The product market setting is defined to be imperfectly competitive if the firm sets a price-cost markup (PMU), which is our model consistent measure of product market power.

Firm i's wage formation process, and, hence, its optimal demand for labor depends on the prevalence and the source of labor market imperfections. The firm's type of competition prevailing in the labor market or its labor market setting (denoted LMS) is defined to be perfectly competitive if the firm engages in marginal product pricing (WMP), that is, pays the marginal employee a real wage equal to her marginal product. Its labor market setting is defined to be imperfectly competitive if the firm either pays a wage markup (WMU), that is, pays the marginal employee a real wage exceeding her marginal product; or sets a wage markdown (WMD), that is, pays the marginal employee a real wage lower than her marginal product.

Intuitively, the perfectly competitive labor market setting ($LMS = WMP$) arises when the wage-employment contract lies on the firm's labor demand curve, which characterizes profit-maximizing employment levels.[7] Analogous to the case of intermediate input, the first-order condition for labor under $LMS = WMP$ is given by setting the marginal revenue

[7] Such solutions arise under either perfect competition in the labor market, in which case the firm unilaterally chooses the profit-maximizing number of workers at the exogenously-given wage or under right-to-manage bargaining (Nickell and Andrews, 1983), in which case the firm unilaterally chooses the profit-maximizing employment level at the bargained wage.

product of labor equal to the price of labor: $(Q_N)_{it} = \mu_{it} \frac{W_{it}}{P_{it}}$. Hence, absent labor market imperfections, there exists no wedge between the output elasticities of intermediate input and labor and their respective revenue shares. Since this wedge is derived using the first-order conditions for output, intermediate input and labor, we call this wedge the firm's joint market imperfections parameter ψ_{it}:

$$\psi_{it} = \frac{(\varepsilon_M^Q)_{it}}{\alpha_{it}^M} - \frac{(\varepsilon_N^Q)_{it}}{\alpha_{it}^N} = 0$$

with $(\varepsilon_N^Q)_{it}$ the output elasticity with respect to labor and $\alpha_{it}^N = \frac{W_{it}N_{it}}{P_{it}Q_{it}}$ the share of labor input expenditure in total revenue.

In contrast to marginal product pricing, labor market imperfections give rise to wage-employment contracts off the firm's labor demand curve. We consider two polar sources of such imperfections. Labor market imperfections may stem from workers' monopoly/bargaining power that forces employers to pay a wage markup ($LMS = WMU$). There exist different underlying theoretical structural models leading to wage-employment contracts above the firm's labor demand curve. Wage-markup pricing may, e.g., arise when (i) a firm and its workforce negotiate simultaneously over wages and employment (McDonald and Solow, 1981), (ii) a firm bargains over wages with a workforce of declining size caused by employees gradually losing their job after bargaining breaks down (Dobbelaere and Luttens, 2016), or (iii) an employee bargains individually over wages with a firm which does not incur hiring costs (Stole and Zwiebel, 1996). Considering the first –widely-used– theoretical structural model, Dobbelaere and Mairesse (2013) show that the first-order condition for labor is given by: $(\varepsilon_N^Q)_{it} = \mu_{it}\alpha_{it}^N - \mu_{it}\gamma_{it}(1 - \alpha_{it}^N - \alpha_{it}^M)$, with $\gamma_{it} = \frac{\phi_{it}}{1-\phi_{it}} \geqslant 0$ the relative extent of rent sharing and $\phi_{it} \in [0, 1]$ the part of economic rents going to the workers or the degree of workers' bargaining power during worker-firm negotiations. ϕ_{it} is our model consistent measure of labor market power under $LMS = WMU$. Hence, the firm's joint market imperfections parameter ψ_{it} under $LMS = WMU$ is equal to:

$$\psi_{it} = \frac{(\varepsilon_M^Q)_{it}}{\alpha_{it}^M} - \frac{(\varepsilon_N^Q)_{it}}{\alpha_{it}^N} = \mu_{it}\frac{\phi_{it}}{1-\phi_{it}}\left[\frac{1 - \alpha_{it}^N - \alpha_{it}^M}{\alpha_{it}^N}\right] > 0$$

Labor market imperfections may also arise from firms' monoposony power that enables them to set a wage markdown ($LMS = WMD$). There exist different underlying theoretical structural models leading to wage-employment contracts below the firm's labor demand curve. Wage-markdown pricing may, e.g., arise when (i) workers have heterogeneous preferences over work environments of different potential employers, (ii) employers collude, or (iii) employers are active in highly concentrated labor markets (Manning, 2003, 2011). Considering the first –widely-used– theoretical structural model, Dobbelaere and Mairesse (2013) show that the first-order condition for labor is given by: $(\varepsilon_N^Q)_{it} = \mu_{it}\alpha_{it}^N\left(1+\frac{1}{(\varepsilon_W^N)_{it}}\right)$, with $(\varepsilon_W^N)_{it} \in \mathbb{R}_+$ the wage elasticity of the labor supply of firm i, measuring the degree of wage-setting power that firm i possesses. $(\varepsilon_W^N)_{it}$ is our model consistent measure of labor market power under $LMS = WMD$. Hence, the firm's joint market imperfections parameters ψ_{it} under $LMS = WMD$ is equal to:

$$\psi_{it} = \frac{(\varepsilon_M^Q)_{it}}{\alpha_{it}^M} - \frac{(\varepsilon_N^Q)_{it}}{\alpha_{it}^N} = -\frac{\mu_{it}}{(\varepsilon_W^N)_{it}} < 0$$

The pricing rules in the product and labor markets lead to six possible regimes of competitiveness $R \in \Re = \{PMC\text{-}WMD,\ PMU\text{-}WMD,\ PMC\text{-}WMP,\ PMU\text{-}WMP,\ PMC\text{-}WMU,\ PMU\text{-}WMU\}$ that we consider. Each corresponds to a combination of the type of competition prevailing in the product market or product market setting $PMS \in \{PMC,\ PMU\}$, and the type of competition prevailing in the labor market or labor market setting $LMS \in \{WMD,\ WMP,\ WMU\}$. These regimes are characterized as subsets of dimension two in the two-dimensional space of the key parameters of our static productivity model, which are the price-cost markup μ_{it} and the joint market imperfections parameter ψ_{it}. Table 1 summarizes the six possible regimes.

<Insert Table 1 about here>

3. Econometric model

In order to obtain consistent estimates of the output elasticicities $(\varepsilon_N^Q)_{it}$ and $(\varepsilon_M^Q)_{it}$, we only consider production functions with (i) a scalar Hicks-neutral productivity term which is observed by the firm but unobserved by the econometrician (denoted by ω_{it}) and (ii) common technology parameters, governing the transformation of inputs to units of output, across a set of producers (denoted by the vector $\boldsymbol{\beta}$). These two assumptions imply the following expression for the production function:

$$Q_{it} = F(N_{it}, M_{it}, K_{it}; \boldsymbol{\beta}) \exp(\omega_{it})\,. \tag{1}$$

Guided by data availability, we cluster producers based on geography and industry. In order to obtain consistent estimates of the production function coefficients ($\boldsymbol{\beta}$) for each of our 28 two-digit industries within each of the three main economic regions in China (which are defined in Section 5), we need to control for unobserved productivity shocks ω_{it}, which are potentially correlated with the firm's input choices. Following Dobbelaere and Kiyota (2018), we apply the estimation procedure proposed by Ackerberg *et al.* (2015) using the insight that optimal input choices hold information about unobserved productivity. We denote the logs of Q_{it}, N_{it}, M_{it} and K_{it} by q_{it}, n_{it}, m_{it} and k_{it}, respectively.

We impose the following timing assumptions. Capital k_{it} is assumed to be decided a period ahead (at $t-1$) because of planning and installation lags. Labor is "less variable" than material. More precisely, n_{it} is chosen by firm i at time $t-b$ ($0<b<1$), after k_{it} being chosen at $t-1$ but prior to m_{it} being chosen at t. This assumption is consistent with firms needing time to train new workers, with firms facing significant hiring or firing costs for labor, or with labor contracts being long term.

We assume that productivity (ω_{it}) evolves according to an endogenous first-order Markov process. In particular, we allow a firm's decision to export (denoted EXP_{it-1}) to endogenously affect future productivity, which is supported by evidence in international economics applications (the Melitz's selection effect; see e.g. Helpman (2006) and Bernard *et al.* (2007, 2012) for reviews of empirical evidence on the positive exporter productivity premium). As such, we can decompose ω_{it} into its conditional expectation given the information known by the firm in $t-1$ (denoted I_{it-1}) and a random innovation to productivity (denoted ξ_{it}):

$$\omega_{it} = \mathbb{E}[\omega_{it}|I_{it-1}] + \xi_{it} = \mathbb{E}[\omega_{it}|\omega_{it-1}, EXP_{it-1}] + \xi_{it} = g(\omega_{it-1}, EXP_{it-1}) + \xi_{it}\,,$$

with $g(\cdot)$ a general function. ξ_{it} is assumed to be mean independent of the firm's information set at $t-1$.

Given these timing assumptions, firm i's intermediate input demand at t depends directly on n_{it} chosen prior to m_{it}, i.e. the input demand function for m_{it} is conditional on n_{it}:

$$m_{it} = m_t(n_{it}, k_{it}, EXP_{it}, \omega_{it})\,. \tag{2}$$

Eq. (2) shows that ω_{it} is the only unobservable entering the intermediate input demand function. This scalar unobservable assumption together with the assumption that $m_t(\cdot)$ is strictly increasing in ω_{it} conditional on n_{it}, k_{it} and EXP_{it} (strict monotonicity assumption)[8], allow to invert ω_{it} as a function of observables:

$$\omega_{it} = m_t^{-1}(m_{it}, n_{it}, k_{it}, EXP_{it})\,. \tag{3}$$

Considering the logarithmic version of Eq. (1) and allowing for an idiosyncratic error term including non-predictable output shocks and potential measurement error in output and inputs (ϵ_{it}) gives:

$$y_{it} = f(n_{it}, m_{it}, k_{it}; \boldsymbol{\beta}) + \omega_{it} + \epsilon_{it}\,,$$

where $y_{it} = q_{it} + \epsilon_{it}$ with ϵ_{it} assumed to be mean independent of current and past input choices.[9]

[8]Levinsohn and Melitz (2002) show that this strict monotonicity assumption holds as long as more productive firms do not set inordinately higher price-cost markups than less productive firms.

[9]Note that $(\varepsilon_N^Q)_{it} = \frac{\partial f(\cdot)}{\partial n_{it}}$ and $(\varepsilon_M^Q)_{it} = \frac{\partial f(\cdot)}{\partial m_{it}}$. These output elasticities are by definition independent of a firm's productivity shock.

We approximate $f(\cdot)$ by a second-order polynomial where all logged inputs, logged inputs squared and interaction terms between logged inputs are included (translog production function):

$$\begin{aligned} y_{it} = \beta_0 + \beta_n n_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{nn} n_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 \\ + \beta_{nm} n_{it} m_{it} + \beta_{nk} n_{it} k_{it} + \beta_{mk} m_{it} k_{it} + \omega_{it} + \epsilon_{it} \,, \end{aligned} \tag{4}$$

where β_0 has to be interpreted as the mean efficiency level across firms.

Substituting Eq. (3) in Eq. (4) results in a first-stage equation of the form:

$$y_{it} = f_{it} + m_t^{-1}(m_{it}, n_{it}, k_{it}, EXP_{it}) + \epsilon_{it} = \varphi_t(n_{it}, m_{it}, k_{it}, EXP_{it}) + \epsilon_{it} \,, \tag{5}$$

which has the purpose of separating ω_{it} from ϵ_{it} , i.e. eliminating the portion of output y_{it} determined by unanticipated shocks at time t, measurement error or any other random noise (ϵ_{it}).

Hence, the first stage involves using Eq. (5) and the moment condition $\mathbb{E}[\epsilon_{it}|I_{it}] = 0$ to obtain an estimate $\widehat{\varphi}_{it}$, of the composite term $\varphi_t(n_{it}, m_{it}, k_{it}, EXP_{it}) = f_{it} + m_t^{-1}(m_{it}, n_{it}, k_{it}, EXP_{it})$, which represents output net of ϵ_{it} . In our application, estimation of Eq. (5) is implemented by regressing output on a second-order polynomial series expansion where all logged inputs, logged inputs squared and interaction terms between logged inputs are included. To allow for time variation in φ_t , these polynomial terms are interacted with a time trend.

Given a particular set of parameters $\boldsymbol{\beta}$, we can compute (up to a scalar constant) an estimate of ω_{it} :

$$\begin{aligned} \widehat{\omega}_{it}(\boldsymbol{\beta}) &= \widehat{m}_t^{-1}(m_{it}, n_{it}, k_{it}, EXP_{it}) \\ &= \widehat{\varphi}_{it} - \beta_0 - \beta_n n_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_{nn} n_{it}^2 - \beta_{mm} m_{it}^2 - \beta_{kk} k_{it}^2 \\ &\quad - \beta_{nm} n_{it} m_{it} - \beta_{nk} n_{it} k_{it} - \beta_{mk} m_{it} k_{it} \,. \end{aligned} \tag{6}$$

In order to implement the second stage and to identify the production function coefficients, we need to recover the innovation to productivity (ξ_{it}) to form moments on. Using Eq. (6), a consistent (non-parametric) approximation to $\mathbb{E}[\omega_{it}|\omega_{it-1}, EXP_{it-1}]$ is given by the predicted values from regressing nonparametrically $\widehat{\omega}_{it}(\boldsymbol{\beta})$ on $\widehat{\omega}_{it-1}(\boldsymbol{\beta})$ and EXP_{it-1} . The residual from this regression provides us with an estimate of ξ_{it} .

Given the timing assumptions on input use, the following population moment conditions can be defined: $\mathbb{E}[\xi_{it}(\boldsymbol{\beta})\boldsymbol{d}] = 0$ where the set of instruments is:

$$\boldsymbol{d}_{it} = \left\{ n_{it-1}, m_{it-1}, k_{it}, n_{it-1}^2, m_{it-1}^2, k_{it}^2, n_{it-1} m_{it-1}, n_{it-1} k_{it}, m_{it-1} k_{it} \right\} \,.$$

Exploiting these moment conditions, we can now estimate the production function coefficients $\boldsymbol{\beta}$ using standard GMM and rely on block bootstrapping for the standard errors. The estimated production function coefficients $\widehat{\boldsymbol{\beta}}$ are then used together with data on inputs to compute the output elasticities at the firm-year level. In particular, we calculate the firm-year elasticity of output with respect to labor as:

$$(\widehat{\varepsilon}_N^Q)_{it} = \widehat{\beta}_n + 2\widehat{\beta}_{nn} n_{it} + \widehat{\beta}_{nm} m_{it} + \widehat{\beta}_{nk} k_{it}\,. \tag{7}$$

Similarly, we calculate the firm-year elasticity of output with respect to material as:[10]

$$(\widehat{\varepsilon}_M^Q)_{it} = \widehat{\beta}_m + 2\widehat{\beta}_{mm} m_{it} + \widehat{\beta}_{mn} n_{it} + \widehat{\beta}_{mk} k_{it}\,. \tag{8}$$

Using the shares of labor and intermediate input expenditure in total sales, α_{it}^N and α_{it}^M, respectively, and our estimates of the output elasticities, $(\widehat{\varepsilon}_N^Q)_{it}$ and $(\widehat{\varepsilon}_M^Q)_{it}$, we are able to compute $\widehat{\mu}_{it}$ and $\widehat{\psi}_{it}$. Since we only observe $Y_{it} = Q_{it} \exp(\epsilon_{it})$, we do not observe the correct expenditure shares for N_{it} and M_{it}. We can recover an estimate of ϵ_{it} from the first stage to adjust the expenditure shares as follows:[11]

$$\widehat{\alpha}_{it}^N = \frac{W_{it} N_{it}}{P_{it} \frac{Y_{it}}{\exp(\epsilon_{it})}}\,, \tag{9}$$

$$\widehat{\alpha}_{it}^M = \frac{J_{it} M_{it}}{P_{it} \frac{Y_{it}}{\exp(\epsilon_{it})}}\,. \tag{10}$$

Using Eqs. (7), (8), (9), and (10), we compute $\widehat{\mu}_{it}$ and $\widehat{\psi}_{it}$ as follows:

$$\widehat{\mu}_{it} = \frac{(\widehat{\varepsilon}_M^Q)_{it}}{\widehat{\alpha}_{it}^M}\,, \tag{11}$$

$$\widehat{\psi}_{it} = \frac{(\widehat{\varepsilon}_M^Q)_{it}}{\widehat{\alpha}_{it}^M} - \frac{(\widehat{\varepsilon}_N^Q)_{it}}{\widehat{\alpha}_{it}^N}\,. \tag{12}$$

4. Classification and testing procedures

4.1. Classification procedure

As explained in Section 2, the characterization of competitiveness regimes is based on the two key parameters of our static productivity model, which are the price-cost markup μ (defined as the gap between the output elasticity with respect to intermediate input and

[10] Under a Cobb-Douglas production function $(\varepsilon_N^Q)_{it}$ and $(\varepsilon_M^Q)_{it}$ would be equal to $\widehat{\beta}_n$ and $\widehat{\beta}_m$, respectively.

[11] This correction is important as it eliminates any variation in expenditure shares that comes from variation in output not correlated with $\varphi_t(\cdot)$.

the share of intermediate input expenditure in total revenue) and the joint market imperfections parameter ψ (defined as the difference in the gap between the output elasticities of intermediate input and labor and their respective expenditure shares).

Estimates of $\widehat{\mu}_{it}$ and $\widehat{\psi}_{it}$ are used to define simultaneously the product market setting and labor market setting of firm i at time t. Different combinations of product and labor market settings classify firm i at time t into a different regime of competitiveness. We apply the classification procedure of Dobbelaere and Mairesse (2013), which is summarized in Table 2.

<Insert Table 2 about here>

4.2. Testing procedure

Ideally, we would like to implement our classification procedure using a testing procedure that identifies exactly the regime of competitiveness for each firm at each year. However, as hypothesis testing is built around the principle of rejecting or not the null hypothesis, we are not able to do so. A priori, we want to be agnostic about a preferred regime and, hence, we want to avoid preferential treatment of any particular regime. To accomplish this, we stick to classical hypothesis testing theory and adopt the following strategy.[12] We take each regime of our classification procedure (see Table 2) sequentially as our null hypothesis and test it using an appropriate test.[13] The intuition behind this strategy is that each regime sequentially is taken to be the truth (that is, adopted as the null hypothesis). We then ask whether there is enough information in the data that supports this claim. The outcome of this strategy is one regime, or potentially a set of regimes, that on the basis of the data cannot be rejected, and, hence, is a/are plausible description(s) of the true regime of competitiveness.

Applying our strategy to the classification procedure outlined above requires implementing a test that is capable of handling nonlinear restrictions on the parameters of the model and testing restrictions under the alternative as well as the null, while taking the dependence between the estimated parameters explicitly into account. We judge that the distance test of Kodde and Palm (1984, 1986) is best equipped to do so, given the flexibility in the type of restrictions on the parameters this test is able to cope with. To identify a firm's

[12] One could also opt for a Bayesian approach and obtain probabilities of a firm being in a specific regime at any point in time. The downside of such approach is that one is not able to classify a firm at each point in time into a specific regime. For that reason and to preserve the link between our estimation and classification procedures, we adopt a classical hypothesis testing approach.

[13] Note that due to differences in null hypotheses between different regimes, we end up with different types of rejection regions for the different regimes. This implies that some regimes are easier to reject when adopted as the truth.

regime of competitiveness at any point in time, the distance test combined with our testing strategy is implemented at the 10% significance level. We define the distance test in formal mathematical terms in Appendix A.

5. Data

We use Chinese firm-level data from the Annual Survey of Industrial Firms (ASIF) conducted by the National Bureau of Statistics (NBS) for the period 1999–2006. This is the most comprehensive and representative firm-level dataset in China, and surveyed firms contribute to the majority of China's industrial value added. The survey includes all industrial firms that are either state-owned or non-state firms with sales above 5 million RMB (Chinese currency).[14] In addition, we use complementary information including industry concordances and detailed price deflators for all nominal variables that capture price evolutions common to all firms in a narrowly defined industry, provided by Brandt *et al.* (2012). We select all firms located in the three most important economic zones in China: the Bohai Bay Economic Rim region surrounding Beijing and Tianjin in the north, the Yangtze River Delta region comprising Shanghai in the east and the Pearl River Delta metropolitan region in the south.

Output (Q) is defined as real gross output measured by nominal production divided by a 4-digit industry output price index. Labor (N) refers to the average number of permanent workers. Material input is defined as intermediate consumption deflated by an intermediate consumption price index. The latter is calculated using the output deflators and information from the 2002 national input-output table. Reflecting the higher level of aggregation of the Chinese input-output table, intermediate input deflators are at the 3-digit level. The capital stock (K) is measured by the real capital stock, computed from tangible assets and investment based on the perpetual inventory method and using the Brandt-Rawski deflator (Perkins and Rawski, 2008) to deflate annual investment. Employee compensation includes wages, employee supplementary benefits, unemployment insurance, retirement benefits, health insurance, and housing benefits. Reported compensation, however, appears to underestimate total payments to labor. The median labor share, defined as the share of value added which is payed out to workers, is only 28.1%. By comparison, the national income accounts suggest a median share of labor around 50%. Therefore, we follow Hsieh and Klenow (2009) and Brandt *et al.* (2012) by inflating the median wage share to half of the value added to approximate the fraction in the national accounts. The shares of labor (α^N) and material input (α^M) are constructed by dividing respectively the firm total labor cost and undeflated intermediate consumption by the firm

[14] Approximately $US 600,000 over this period, a time when manufacturing prices were relatively stable.

undeflated production.

We focus only on manufacturing firms, assigning firms to 28 two-digit industries within each of the three considered economic regions. We deleted observations with cost shares greater than or equal to one and smaller than or equal to zero. We also disregarded observations with top and bottom 1 percentiles in industry-year cost shares to remove outliers. We selected firms that survive at least four consecutive years because lagged inputs are needed to construct moment conditions in our estimation framework. Our estimation sample consists of 57,577 firms. Table B.1 in Appendix B reports the panel structure of the estimation sample. Table B.2 reports the number of observations and firms by industry. Table 3 reports the means, standard deviations, and quartile values of the main variables in our estimation sample.

<Insert Table 3 about here>

To identify the impact of trade liberalization on the prevalence and intensity of product and labor market power, we exploit variation in tariff reductions across industries, following Lu and Yu (2015) and Brandt *et al.* (2017). In early 2002, China started to fulfill its tariff reduction responsibilities as a WTO member. According to the WTO accession agreement, China was required to complete tariff reductions by 2004. We exploit the fact that industries that have previously been more protected (i.e. with higher tariffs) experienced greater tariff reduction under the WTO agreement and therefore higher degrees of liberalization whereas previously more open industries (i.e. with lower tariffs) witnessed small tariff reductions and therefore less liberalization. Presumably, China was required to reduce tariffs to WTO-determined levels, which are quite uniform across products, whereas pre-WTO tariff levels varied widely across products. As a consequence, both the average and dispersion of tariffs across industries fell.

Product-level tariff rates at the 8-digit level of the Harmonized System product classification are mapped into China's Industrial Classification (CIC) system at the 4-digit level to obtain output tariffs that we use in the firm-level analysis. Input tariffs are a weighted average of output tariffs, using industry shares from the off-diagonal elements of the 2002 input-output table as weights. Given that the input-output table is defined at the 3-digit level, so are the input tariffs. Over the period 1998–2006, average output tariffs fell from close to 20% to nearly 9%, whereas average input tariffs dropped from slightly over 15% to just above 7%. Hence, we observe not only tariff compression within each tariff type, but also a narrowing gap between the two tariff types.

6. Regimes of competitiveness

6.1. Inconclusiveness of the distance test

As explained in Section 4, the identification of a firm's competitiveness regime at any point in time is based on implementing the distance test, which takes the dependence between a firm's product market setting and its labor market setting explicitly into account.

The distance test is inconclusive in identifying a firm's regime of competitiveness at any point in time in 44% of the cases. In 72% of these inconclusive cases, the test is in doubt between two regimes.

Let us now explore the nature of this inconclusiveness. We estimated a probit model including several firm characteristics —such as capital intensity, size (number of workers) and ownership type— industry fixed effects, regional fixed effects and a pre-WTO period indicator. We find that industry fixed effects are the driving source of the observed inconclusiveness. Ownership type and regional fixed effects seem to play only a minor role. As such, we conclude that firm characteristics neither significantly nor economically explain the observed inconclusiveness of the distance test.

Recall that we define market boundaries based on geography and industry, that is, we estimate the translog production function coefficients for each of our 28 two-digit industries within each of the three considered economic regions. One potential reason for explaining the role of industry fixed effects in driving the inconclusiveness could be industry size. This is because the precision of the production function estimates determines the precision of the output elasticities with respect to labor and intermediate input and, hence, the precision of the key parameters of our static productivity model, μ and ψ (see Eqs. (11)–(12)). This, in turn, determines the outcome of the distance test. In order to determine whether this precision varies by industry size, we perform a variance decomposition on the difference in variance of the output elasticities for large and small industries. In this decomposition, we consider the difference in the average variance for a large and a small industry and decompose this difference into two components. The first component corresponds to the difference in precision of the production function estimates, keeping the input factors constant at the large-industry average. The second component corresponds to the difference in input factors, keeping the precision of the production function estimates at the level of the small industry. Such decomposition can be interpreted as separating the difference in variance into (i) a component related to the difference in precision due to different sample sizes and (ii) a component related to the difference in input factors which also affects the variance of the output elasticities through the translog functional form of the production function. This variance-decomposition is done pair-wise for each small-large industry combination. In general, differences in precision of the translog production function coefficients account for more than 80% of differences in precision of the output elasticities between a large and small industry. These findings are robust to classifying small industries as falling below the 25th-, 50th-, or 75th-percentile of the industry size distribution.

Let us now turn to the composition of inconclusiveness at the industry level. We observe that a large fraction of inconclusive cases arises due to inconclusiveness between two regimes of competitiveness. Figure 1 shows that there is large heterogeneity across industries in terms of both the level and composition of the inconclusiveness. The inconclusive cases are composed of inconclusiveness between more than two regimes and inconclusiveness between two regimes, which we label as severe and mild inconclusiveness, respectively.

<Insert Figure 1 about here>

Figure 2 shows, in line with the results from the probit model and the variance decomposition, that industry size is an important determinant of inconclusiveness at the industry level. More specifically, there appears to be a strongly negative relationship between inconclusiveness and industry size. Figure 2 also reveals that there is a gap for small industries compared to medium–large industries between total inconclusiveness and inconclusiveness between two regimes. For medium and large industries, inconclusiveness between two regimes accounts for 80–90% of total inconclusiveness, while for small industries this fraction is around 50–60%.

<Insert Figure 2 about here>

Recall that a firm's regime of competitiveness at any point in time corresponds to a combination of the type of competition prevailing in the product market or product market setting, and the type of competition prevailing in the labor market or labor market setting. To explore the importance of each market setting in driving the inconclusiveness of the distance test in identifying a firm's regime of competitiveness, Figure 3 shows inconclusiveness due to inconclusiveness related to the product (labor) market setting conditional on being able to identify the labor (product) market setting. We observe that, conditional on being able to identify the product market setting, the labor market setting is identified as well in almost all cases, i.e. conditional on conclusiveness on the product market setting there is almost no inconclusiveness on the labor market setting. Figure 3 shows that this does not hold for conditional inconclusiveness of the product market setting. Conditional on being able to identify the labor market setting, the inconclusiveness on the product market setting is 50–70% for small industries and goes down to around 20% for large industries. As such, we observe that almost all inconclusiveness between two regimes is driven by conditional *PMS*-inconclusiveness. The intuition is that, in reality, firms seldom operate under a theoretical extreme of the product market setting spectrum. For example, firms might be able to exercise market power on some market segments and not on others. Hence, intuitively total inconclusiveness is driven by the fact that we only consider two (extreme) product market settings.

<Insert Figure 3 about here>

6.2. Stability of regimes of competitiveness

The panel nature of the data enables us to investigate time variation in a firm's regime of competitiveness over the period 2000–2006. Given the large number of firms, we present results at the industry level which we obtain by aggregating the firm-year results. More specifically, the firm-year number of occurrences are aggregated at the industry level by summing up the firm-year level occurrences weighted by the share of value added for all firms within the industry, i.e.:

$$\sum_{i \in \mathfrak{J}} w_i \, (\# \text{ of occurrences of regime } R) \; ,$$

where $\mathfrak{J}$ denotes the set of firms contained in industry j and w_i denotes the weight defined as the share of value added of firm i. The weighted frequencies of occurrence of competitiveness regimes are obtained by dividing the aggregated weighted number of occurrences by the weighted number of observations within the industry, i.e.:

$$\frac{\sum_{i \in \mathfrak{J}} w_i \, (\# \text{ of occurrences of regime } R)}{\sum_{i \in \mathfrak{J}} w_i} \, .$$

The prevailing regime at the industry level is the regime that has the highest frequency of occurrence. Since this prevailing industry-specific regime masks time variation in dominant regimes for a particular industry, we first look at the evolution of industry-specific dominant regimes over time. This is accomplished by aggregating firm-year number of occurrences at the industry-year level using the same weighted sum as discussed above. The dominant industry-year regime is the regime with the highest weighted frequency of occurrence. When the maximum weighted frequency occurs at multiple regimes, the first regime encountered is chosen to be the dominant regime.

Table 4 presents variation in regimes of competitiveness over the period 2000–2006 at the industry level. We find that 25% of industries (7 out of 28) observe at least one change in their regime of competitiveness over time. This apparent stability suggests that the impact of WTO membership on regime switches is relatively modest. Besides, some of the switches in regimes over time that do occur are caused by the inconclusiveness of the distance test, i.e. for some firms and years the distance test is not able to identify a single regime of competitiveness.

<Insert Table 4 about here>

Let us now turn to the regimes of competitiveness that prevail in each of the 28 industries, which we present in Table 5. The frequencies are denoted as fractions and are ranked according to an industry's dominant regime and within the dominant regime on the basis of the highest weighted frequency of occurrence. These frequencies may not necessarily sum up to 1 due to the inconclusiveness of the distance test.

<Insert Table 5 about here>

Table 5 reveals that perfect competition in both product and labor markets is not very common across Chinese manufacturing industries, with an average fraction of occurrence well below 0.10. This confirms expectations as the *PMC-WMP* regime of competitiveness is often thought to be a philosophical benchmark. The two predominant regimes of competitiveness at the industry level are *PMU-WMU* and *PMU-WMD*, with an average fraction of occurrence above 0.90 for the former and about 0.28 for the latter. These predominant regimes indicate that most industries operate under imperfect competition in product and labor markets, they seem to differ mainly in their labor market setting. The large fraction of occurrence of the *PMU-WMU* regime is compatible with recent evidence on the role of workers' bargaining power in shaping the wage distribution in China over the period 2000–2007. This, in turn, could be related to risk sharing (Duan and Martins, 2019) or fair wage (Kamal *et al.*, 2015) arguments. Given that many formal labor market institutions (such as collective bargaining, independent trade unions, forms of social protection) are still at a relatively early stage of development, our findings are far less likely explained by effective union bargaining power. Indeed, trade unions are indirectly controlled by the government and China's communist party through their affiliation with the single national organization (the All-China Federation of Trade Union, ACFTU). There is, however, evidence on the collective voice role of Chinese unions, including mediating labor disputes, monitoring implementation of the Labor Law and promoting employee training, which is also compatible with our results (Lu *et al.*, 2010; Budd *et al.*, 2014). Confirming expectations, a large fraction of firms that set wage markdowns ($LMS = WMD$) are state-owned enterprises (SOEs).

Let us now discuss the volatility of competitiveness regimes at the industry level. Regime changes at the firm level are determined by comparing the regime of the first year available for firm i with that of the final year available, i.e. $R_{iT} - R_{i0}$, where T and 0 denote respectively the final and first year available for firm i. The firm-level average changes in regime are aggregated at the industry level. The variation of the average change in regime of competitiveness at the industry level is visualized in Figure 4, where industries are ranked by the number of firms within each industry. Each circle represents an industry, where the center of the circle denotes the average change and the radius corresponds to a measure of variation (standard deviation) of the average change. Table B.3 in Appendix B presents the average change in regime of competitiveness at the industry level and within-industry variation underlying Figure 4.

<Insert Figure 4 about here>

Figure 4 clearly shows that industry size does not have an effect on the average number of regime changes at the industry level. The average change lies just below one, with not much variation across industries. However, there is more variability in the standard deviation of the average change: some industries display a standard deviation just short of two, while some others have little to no variation. This within-industry variation could be explained by differential effects of WTO entry on different subgroups within industries, which we examine in the next sections.

7. Impact of WTO accession on the prevalence of product and labor market imperfections at the firm level

7.1. Descriptive analysis of WTO entry effect

Let us now turn to discussing time variation in competitiveness regimes in light of China's accession to the WTO at the end of 2001. WTO membership might have exerted positive effects on the Chinese domestic economy. There are various channels through which trade policy changes might impact competition among sellers in goods markets. Input tariff liberalization reduces firms' marginal costs through lowering input prices or increasing technical (within-firm) efficiency via an increase in access to imported intermediate inputs of higher quality and broader variety. Output tariff liberalization directly exposes firms to intensified import competition through changing the residual demand they face, either through shifting residual demand curves of survivors down, or through increasing the demand elasticity that domestic firms perceive. This direct procompetitive effect causes firms to adjust by lowering price-cost markups. Output tariff liberalization might also exert an indirect effect through hiring better managers or changing the organization structure, thereby reducing X-inefficiencies and increasing within-firm productivity. Which effect dominates, is a priori not clear. Firm i's price-cost markup (μ_{it}) is a principal input in the characterization of its regime of competitiveness: it determines its product market setting and is a component of its joint market imperfections parameter (ψ_{it}), which determines its labor market setting. For example, a strong downward pressure on price-cost markups would induce a shift towards the *PMC*-product market setting.

The impact of WTO membership on a firm's labor market setting is a priori not clear, either. High-productive (and thus high-profit) firms might be more willing to share rents with their workers according to a surplus-sharing rule and to pay wage markups, yielding an increase in the frequency of *WMU*-labor market setting occurrences. On the other hand, high-productive (low marginal-cost) firms might expand their market share. Larger firms might be less likely to negotiate and more willing to use wage posting because they can better process the larger pool of applicants created if recruitment technology is better in large firms, or large firms might exert more control over local wages, yielding an increase in the frequency of *WMD*-labor market setting occurrences.

To study these effects, Table 6 reports the difference-in-differences in weighted frequency of occurrence of each regime compared to the pre-WTO dominant regime of competitiveness at the industry level before WTO entry (years 2000–2001) and after WTO entry (years 2002–2006), i.e.:

$$\Delta\left(\frac{\sum_{i\in\mathfrak{I}} w_i \left[(\#\text{ of occurrences of regime } R) - (\#\text{ of occurrences of regime } \hat{R})\right]}{\sum_{i\in\mathfrak{I}} w_i}\right),$$

where $\hat{R}$ denotes the pre-WTO dominant regime. Δ denotes the difference operator, defined as the difference between the post-WTO period and pre-WTO period.

<Insert Table 6 about here>

Such difference-in-differences approach allows us to provide suggestive evidence on the impact of WTO accession on switches in industries' pre-WTO dominant regime of competitiveness. A large absolute value of the difference-in-differences change of certain regimes would suggest an impact of WTO membership on the regime of competitiveness in which firms/industries operate.[15,16] In order to highlight the importance of observed changes, we mark regimes in Table 6 as follows. * marks a regime displaying a difference-in-differences

[15]This difference-in-differences change entails a compositional effect as well as an WTO accession effect. The compositional effect consists of changes in firms belonging to a specific regime during the period 2000–2006. The WTO accession effect refers to time variation in regimes due to trade liberalization. Isolating the impact of WTO accession on regimes of competitiveness requires disentangling both effects, which we indirectly do in Section 7.2.

[16]Besides the issue of disentangling compositional from WTO accession effects, this difference-in-differences analysis could be biased as we have abstained from adjustment costs in our theoretical model in Section 2. As can be shown, ruling out adjustment costs leads to overestimating price-cost markups and, hence, overestimating *PMU*- and underestimating *WMD*-incidence (derivations available upon request).

change exceeding 25 percentage points in absolute value, † marks a regime that is more than 10 percentage points apart from the pre-WTO dominant regime prior to WTO entry and less than 10 percentage points apart after WTO entry, ‡ marks a regime that is less than 10 percentage points apart from the pre-WTO dominant regime prior to WTO entry and more than 10 percentage points apart after WTO entry and $^{\diamond}$ marks a change in the dominant regime, i.e. a regime different from the pre-WTO dominant regime that has become the dominant regime in the post-WTO period.

Table 6 reveals little heterogeneity in WTO entry effects across regimes. Only a handful of changes are observed which may have influenced the identification of the dominant regime after WTO accession.[17] Moreover, we only observe for one industry a switch in dominant regime in the post-WTO period, which is consistent with the stability of regimes over time documented in Section 6.2. Focusing on the product market, we find that the most relevant changes are in favor of the imperfectly competitive setting (PMU). PMU appears to be the dominant product market setting in both the pre-WTO and post-WTO periods. This suggests that the most likely beneficiaries of trade liberalization in the short run are domestic firms that benefit from lower production costs while simultaneously raise price-cost markups. Focusing on the labor market, we mostly observe a strengthening of the pre-WTO labor market setting. As such, we mainly find a consolidation of pre-WTO dominant regimes after WTO accession. Hence, we do not find suggestive evidence for a decline in (factor) price distortions after trade liberalization, i.e. we do not observe a trend towards a perfectly competitive product/labor market setting (PMC/WMP). Recall that these are market settings in which firms set prices equal to marginal costs/pay real wages equal to the marginal product of labor, and hence, do not exert product/labor market power.

7.2. Impact of WTO entry on switching away from exerting product/labor market power

In order to identify the effect of trade liberalization on the prevalence of market power at the firm level, we perform a switcher analysis. Such analysis aims at estimating the impact of trade liberalization on the likelihood of switching away from an imperfectly competitive product/labor market setting, i.e. switching away from exerting product/labor market power. To do so, we divide firms into stayers and switchers for a specific product/labor market setting. This stayer-switcher distinction allows us to identify the effect of trade liberalization conditional on the pre-WTO product/labor market setting, and, hence, the impact of trade liberalization on the likelihood of switching away from the pre-WTO prod-

[17] These changes are marked with †, ‡, or $^{\diamond}$.

uct/labor market setting in the post-WTO period relative to staying in the pre-WTO product/labor market setting.

Firms belong to the category of stayers if their pre- and post-WTO product/labor market setting is the same. Firms are categorized as switchers if their pre-WTO product/labor market setting is different from their post-WTO product/labor market setting, where switching behavior is relative to the pre-WTO product/labor market setting. For example, an *WMU*-switcher is a firm that switches from an *WMU*-labor market setting in the pre-WTO period to either a *WMP*- or *WMD*-labor market setting in the post-WTO period.[18]

Identifying the effect of trade shocks on market power at the firm level requires dealing with the inconclusiveness of the distance test by applying an allocation rule. More specifically, we first select all conclusive cases and the subset of inconclusive cases in which the distance test is inconclusive between either two or three regimes. Such mild inconclusiveness amounts to 80% of the inconclusive cases.[19] Second, if —conditional on this selection— a firm has a dominant product/labor market setting in the pre-WTO period (years 2000-2001), we assign the dominant product/labor market setting to that inconclusive (hence, missing) product/labor market setting. We define a firm's dominant product/labor market setting in the pre-WTO period based on the highest frequency of occurrence. Our core set of results are robust to not applying such allocation rule.[20]

In our switcher analysis, we apply the allocation rule to the pre- and post-WTO period separately. If the distance test produces inconclusive results in the pre- or post-WTO period, we, hence, assign the product/labor market setting for which we have most evidence.

We postulate that firm i's product market setting at time t might depend on the degree of trade liberalization, other observable characteristics as well as unobservable factors ϵ such as managerial ability. Suppressing firm and time subscripts (i and t, respectively) for simplicity, we thus have:

$$PMS^* = \beta_0 + \beta_1 \text{input tariff} + \beta_2 \text{output tariff} + \boldsymbol{z}'\beta_z + \epsilon \,, \tag{13}$$

where input tariff and output tariff denote the 1-year lagged values of the policy variables input tariffs and output tariffs, respectively. To control for two ongoing policy reforms in the early 2000s, SOEs reform and relaxation of foreign-direct investment (FDI) regulations,

[18]Note that switching from *WMU* to *WMD* is a hypothetical example as such switches are rare. The same holds for *WMD*-to-*WMU* switches.

[19]The composition of inconclusiveness for this subset is shown in Figure B.2 in Appendix B. The inconclusiveness and conditional inconclusiveness as a function of industry size are depicted in Figures B.3 and B.4, respectively.

[20]Results not reported but available upon request.

the vector $\boldsymbol{z}$ comprises industry-year varying variables such as the share of state-owned sales and the share of foreign-owned sales in total sales. It also includes a firm's size (number of workers) and a full set of year fixed effects in order to control for macroeconomic shocks common to all firms.

In order to investigate the link between the degree of trade liberalization and the likelihood of switching away from imperfect competition in the product market (that is, exerting product market power), we specify the following probit model:

$$\mathbb{P}(PMU\text{-switch} \mid \boldsymbol{x}) = \Phi(\boldsymbol{x}'\beta)\,. \tag{14}$$

The vector $\boldsymbol{x}$ includes the regressors specified in Eq. (13).

Whether market power in firm i in period t is consolidated on either the demand side or the supply side of labor might be influenced by common observable as well as unobservable factors such as a firm's corporate culture. In order to investigate the link between the degree of trade liberalization and the likelihood of switching away from imperfect competition in the labor market (that is, either setting a wage markdown or paying a wage markup), we specify the following univariate probit models:

$$\begin{aligned} LMS_m^* &= \boldsymbol{x}_m'\beta_m + \epsilon_m\,, \qquad && m = 1,2 \\ LMS_m &= I(LMS_m^* > 0)\,, && m = 1,2 \end{aligned}$$

where $LMS_1 = \mathbb{P}(WMD\text{-switch} \mid \boldsymbol{x})$ and $LMS_2 = \mathbb{P}(WMU\text{-switch} \mid \boldsymbol{x})$. We include the same regressors as in the univariate probit model defined in Eq. (14).

The results of this switcher analysis are reported in Table 7. Columns 1, 4 and 7 present the marginal effect of our main regressors on the probability of switching away from the pre-WTO period product/labor market setting relative to staying in the pre-WTO period product/labor market setting in the univariate probit models. More specifically, column 1 reports how much the conditional probability of switching away from $PMS = PMU$ in the post-WTO period relative to staying changes when the value of a regressor changes, holding all other regressors constant whereas column 4 (7) shows how much the likelihood of switching away from $LMS = WMD$ ($LMS = WMU$) in the post-WTO period relative to staying changes. Accounting for heteroskedasticity and arbitrary autocorrelation, we cluster standard errors at the four-digit industry-year level (level of treatment) for statistical inference and use within-industry and between-industry output share weights in all regressions.

<Insert Table 7 about here>

Our main finding is that, in general, trade liberalization via tariff reductions has not exerted a statistically and economically significant effect on shifting the prevalence of firms' market imperfections, that is, shifting firms away from an imperfectly competitive product or labor market setting relative to staying. This finding is consistent with our descriptive difference-in-differences results and indicates that the normality assumption underlying the probit models is not driving our results, as our difference-in-differences approach can be seen as the non-parametric counterpart to this probit analysis.

The marginal effects for the product market could be explained by the fact that only a small fraction of firms switches towards perfect competition in the product market. Moreover, only a small fraction of firms at any point in time is characterized by perfect competition in the product market.

At first sight, we tend to conclude that trade policy changes via tariff reductions has strongly affected the likelihood that firms shift away from setting wage markdowns. However, these marginal effects are driven by a very specific and small subset of firms (see Section 8). For these firms, a 1-percentage-point reduction in tariffs on intermediate inputs decreases the conditional probability of *WMD*-switch by 20 percentage points while a 1-percentage-point reduction in output tariffs increases the conditional probability of *WMD*-switch by 9 percentage points. The marginal effects for the labor market show an economically small negative impact of input tariff cuts on the likelihood of switching away from paying wage markups: a 1-percentage-point reduction in tariffs on intermediate inputs decreases the conditional probability of *WMU*-switch by 3 percentage points.

To check robustness, we estimate the average effect of tariff reductions (and other dependent variables) on switching away from an imperfectly competitive product/labor market setting in a "representative enterprise" (see columns 2, 5 and 8 in Table 7). We also present TSLS estimates in which we use tariff rates from the WTO agreement (predetermined maximum tariff rates) as instruments for actual tariff rates in the post-WTO period to rule out a policy endogeneity concern associated with using nominal tariffs as reflecting the degree of government intervention (see columns 3, 6 and 9 in Table 7). Estimating these linear probability models leads to similar conclusions as estimating the probit models discussed above.

There are two main sources that could drive a wedge between output elasticities of labor and intermediate inputs and their respective expenditure shares in revenue: market imperfections and factor adjustment costs. As we abstained from adjustment costs in our theoretical model, we could potentially have biased results in our switcher analysis. However, we use tariff cuts for identification of the effect of trade liberalization on product and labor market settings. Hence, as long as changes in adjustment costs are uncorrelated with changes in tariffs, our results are not affected. As the tariff reductions are thought to be exogenous changes, it is indeed likely that adjustment cost changes are uncorrelated with tariff cuts, which is supported by our TSLS estimates.

8. Impact of WTO accession on the intensity of product and labor market imperfections at the firm level

In the previous section, we have investigated the effect of trade liberalization on the prevalence of imperfections in product and labor markets. In particular, we have examined the impact on the probability of switching away from setting price-cost markups, and setting wage markdowns/paying wage markups. From a policy perspective, it is equally important to understand whether trade liberalization in intermediate-inputs and final-goods industries has affected the intensity of product and labor market imperfections. To identify such effects, we estimate the average impact of input and output tariff reductions (and other independent variables) on the magnitude of price-cost markups and the magnitude of wage markdowns/wage markups, conditional on the relevant product/labor market setting.

In order to give a structural interpretation of the magnitude of firms' product and labor market power, we focus in this section on widely-used models of imperfect competition. Consistent with standard models of imperfect competition in the product market, we measure the magnitude of a firm's product market power by its price-cost markup μ_{it}. Consistent with two widely-used models of imperfect competition in the labor market, we measure the magnitude of labor market power either by the wage elasticity of a firm's labor supply curve $(\varepsilon_W^N)_{it}$ in the case of wage markdown-pricing or the workers' bargaining/monopoly power ϕ_{it} in the case of wage markup-pricing (see Section 2). Both $(\varepsilon_W^N)_{it}$ and ϕ_{it} are transformations of a firm's wage markdown and a firm's wage markup, respectively.[21] As such, we define the following regression models:

$$\ln \widehat{\mu}_{it} = \alpha_0 + \alpha_1 \text{input tariff}_{jt-1} + \alpha_2 \text{output tariff}_{jt-1} + \alpha_3 IMR_{it} + \alpha_i + \boldsymbol{z}'\alpha_z + \zeta_{it}\,,$$

$$\ln(\widehat{\varepsilon}_W^N)_{it} = \alpha_0 + \alpha_1 \text{input tariff}_{jt-1} + \alpha_2 \text{output tariff}_{jt-1} + \alpha_3 IMR_{it} + \alpha_i + \boldsymbol{z}'\alpha_z + \zeta_{it}\,,$$

$$\ln\left(\frac{\widehat{\phi}_{it}}{1-\widehat{\phi}_{it}}\right) = \alpha_0 + \alpha_1 \text{input tariff}_{jt-1} + \alpha_2 \text{output tariff}_{jt-1} + \alpha_3 IMR_{it} + \alpha_i + \boldsymbol{z}'\alpha_z + \zeta_{it}\,,$$

with IMR the inverse Mills ratio from the respective probit model which we include to account for selection bias, α_i firm fixed effects, and the vector $\boldsymbol{z}$ comprising the same

[21] $(\varepsilon_W^N)_{it}$ is a direct transformation of a firm's wage markdown as there exists a 1-1 relationship: a higher $(\varepsilon_W^N)_{it}$ implies a narrower wage markdown. ϕ_{it} is an indirect transformation: a higher ϕ_{it} implies a higher wage markup.

regressors as in the switcher analysis. As before, we instrument applied tariffs in the post-WTO period with predetermined maximum tariff rates. As the share of rents captured by the workers (ϕ) lies within the $[0, 1]$-range, we use a logit transformation to model the degree of workers' bargaining power during worker-firm negotiations. As before, one could be worried about the validity of this analysis due to the potential presence of adjustment costs. However, the same argument applies as made in Section 7.2, that is, our results are not biased by ignoring adjustment costs in our theoretical model because tariff reductions are exogenous.

Table 8 presents the average effect of the regressors in the three regression models. Most importantly, our results provide evidence of trade liberalization in intermediate-inputs industries having affected the intensity of firms' product versus labor market power differently. Conditional on setting price-cost markups ($PMS = PMU$), we find that a reduction in input tariffs increases the degree of product market power (price-cost markups), as expected. This result is in line with Brandt *et al.* (2017) who find that cuts in input tariffs raise both price-cost markups and productivity. More specifically, each percentage point decline in tariffs on intermediate inputs increases a firm's price-cost markup by 0.8 percent. Conditional on setting wage markdowns ($LMS = WMD$), each percentage point decline in input tariffs is found to decrease a firm's wage-setting power by 7.5 percent.

<*Insert Table 8 about here*>

The decline in firms' wage-setting power, conditional on setting wage markdowns, might especially be pronounced in SOEs, as part of the WTO accession conditions was to privatize these SOEs. We confirm this conjecture in Table B.4 in Appendix B: each percentage point decline in input tariffs decreases the wage-setting power of a state-owned firm by 13 percent, which is almost twice as large as compared to conditioning on firms that set wage markdowns. When we condition on SOEs that set wage markdowns ($LMS = WMD$) we find that a percentage point decline in input tariffs leads to a reduction in a firm's wage-setting power by 11 percent (see columns 3 and 4 in Table B.4). Hence, a large fraction of the effect of trade liberalization on the wage-setting power of firms is driven by SOEs.

At first sight, the negative impact of trade liberalization in intermediate-inputs industries on firms' wage-setting power seems inconsistent with the negative impact found on the probability of switching away from setting wage markdowns (see Section 7.2). As already alluded to in Section 7.2, the subset of firms that switch away from setting wage markdowns might be very different from the average wage-setting firm as we observe only a handful of such switches. Table B.5 in Appendix B confirms that this is indeed the case: the effect of input tariff reductions on the degree of wage-setting power for this very specific (and small) subset of firms is completely opposite to the above documented effect for the average wage-setting firm. Hence, this again confirms that trade liberalization has not induced firms to switch away from an imperfectly competitive product/labor market setting.

So far, our results could potentially capture the impact of trade liberalization on the intensity of market imperfections at the firm level (true trade liberalization effect) as well as on firms' switching behavior (compositional changes within a particular product/labor market setting). In order to isolate the true impact of trade policy changes on market power, we condition on being a stayer for the relevant product/labor market setting. Table 9 reports the average effect of our regressors of interest for the subsample of stayers and, hence, reveals true trade liberalization effects.

<Insert Table 9 about here>

From Table 9, it follows that, in general, the sign and magnitude of the input and output tariff effects are similar to the ones reported in Table 8. This indicates that compositional effects are not driving our results discussed above.

Modeling the dependence between pricing rules in the product market and in the labor market allows us to analyze potential heterogeneous effects of trade liberalization on the intensity of product/labor market power at the firm level. We do so by estimating the impact of trade shocks on the intensity of product market imperfections (price-cost markups) conditional on setting wage markdowns ($LMS = WMD$) and by estimating such impact on the intensity of labor market imperfections (wage-setting power) conditional on setting price-cost markups ($PMS = PMU$). The results of these heterogeneous effects are reported in Table 10 and visualized in Figure B.1 in Appendix B.

<Insert Table 10 about here>

Comparing Tables 8 and 10 shows that the negative effect of input tariffs on the intensity of product market imperfections is more pronounced for firms that exert labor market power ($LMS = WMD$) than for firms that exert product market power ($PMS = PMU$). Moreover, besides an effect that runs through the intermediate input channel of trade, we now also observe a small procompetitive effect via output tariff reductions on the magnitude of price-cost markups. Conditional on exerting labor market power ($LMS = WMD$), each percentage point decline in input (output) tariffs is found to increase a firm's price-cost markup by roughly 1 (0.15) percent. Likewise, comparing Tables 8 and 10 reveals that the negative impact of falling input tariffs on firms' wage-setting power is stronger for firms that have market power in the product market ($PMS = PMU$). We again conclude that compositional effects are not driving these results (see Table B.6 in Appendix B).

9. Conclusion

How does firms' pricing behavior in product and labor markets respond to domestic trade liberalization? In spite of its importance for understanding the distributional consequences of trade shocks and the underlying sources of increased interfirm wage disparities, this question has not been answered so far. This paper examines the impact of trade liberalization in intermediate-inputs and final-goods industries on the prevalence and intensity of product and labor market power of Chinese manufacturing firms.

We generalize the model of De Loecker and Warzynski (2012) for obtaining a measure of firms' product market power (price-cost markup). Relaxing their standard cost-minimization assumption allows us to consider two polar models of wage formation in imperfect labor markets: one where workers' monopoly power forces employers to pay a wage markup and one where firms' monopsony power enables them to set a wage markdown. Our model takes the dependence between pricing rules in product and labor markets explicitly into account.

We use production data on Chinese manufacturing firms to estimate the prevalence and intensity of product and labor market power over the period 1999–2006. We then examine whether China's membership to the World Trade Organization in 2001 has affected the product and labor market power of Chinese firms. As such, our application can be considered as a generalization of Brandt *et al.* (2017) who examine the impact of trade liberalization via input and output tariff reductions on the magnitude of price-cost markups (and productivity) of Chinese firms.

We find that trade liberalization has not affected the prevalence of price-cost markups and wage markups/wage markdowns. More specifically, tariff reductions have not switched firms away from exercising product and labor market power. However, trade liberalization has affected the intensity of price-cost markups and wage markdowns. In particular, tariff cuts on intermediate inputs have increased a firm's price-cost markup but decreased the degree of wage-setting power that it possesses, conditional on exercising product/labor market power respectively. In the Chinese context, the narrowing effect of input tariff cuts on wage markdowns can be linked to the fall of wage-setting power of state-owned enterprises, which we confirm.

Besides disentangling the impact of trade shocks on product and labor market power, another advantage of modeling the dependence between pricing rules in product and labor markets is that we are able to reveal heterogeneous trade liberalization effects on the intensity of firms' product and labor market power. We show that input tariff reductions have predominantly increased the product market power (price-cost markup) of firms that exercise labor market power (set wage markdowns). Such tariff cuts have predominantly decreased the labor market power (wage-setting power) of firms that exercise product market power (set price-cost markups).

In terms of broader implications, we view the joint responses of firms' pricing behavior in product and labor markets to trade policy changes together with the heterogeneous trade liberalization effects as an important step towards understanding the true consequences of trade shocks.

References

Ackerberg, D. A., K. Caves, and G. Frazer. 2015. Identification properties of recent production function estimators. *Econometrica* 83(6): 2411–2451.

Beale, E. M. L. 1955. On minimizing a convex function subject to linear inequalities. *Journal of the Royal Statistical Society. Series B (Methodological)* 17(2): 173–184.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott. 2007. Firms in international trade. *Journal of Economic Perspectives* 21(3): 105–130.

— 2012. The empirics of firm heterogeneity and international trade. *Annual Review of Economics* 4(1): 283–313.

Bohrer, R. and W. Chow. 1978. Algorithm AS 122: Weights for one-sided multivariate Inference. *Journal of the Royal Statistical Society. Series C (Applied Statistics)* 27(1): 100–104.

Brandt, L., T. Tombe, and X. Zhu. 2013. Factor market distortions across time, space and sectors in China. *Review of Economic Dynamics* 16(1): 39–58.

Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang. 2017. WTO accession and performance of Chinese manufacturing firms. *American Economic Review* 107(9): 2784–2820.

Brandt, L., J. Van Biesebroeck, and Y. Zhang. 2012. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics* 97(2): 339–351.

Brandt, L. and X. Zhu. 2010. Accounting for China's growth. Working Paper 394. University of Toronto.

Branstetter, L. and N. Lardy. 2008. "China's embrace of globalization". In: *China's economic transition: Origins, mechanisms, and consequences*. Ed. by L. Brandt and T. G. Rawski. Cambridge University Press. Chap. 13, 633–682.

Budd, J. W., W. Chi, Y. Wang, and Q. Xie. 2014. What do unions in China do? Provincial-level evidence on wages, employment, productivity, and economic output. *Journal of Labor Research* 35(2): 185–204.

Chen, S. and M. Ravallion. 2004. Welfare impacts of China's accession to the World Trade Organization. *World Bank Economic Review* 18(1): 29–57.

Dardanoni, V. and A. Forcina. 1998. A unified approach to likelihood inference on stochastic orderings in a nonparametric context. *Journal of the American Statistical Association* 93(443): 1112–1123.

De Loecker, J. and P. K. Goldberg. 2014. Firm performance in a global market. *Annual Review of Economics* 6(1): 201–227.

De Loecker, J. and J. Van Biesebroeck. 2018. "Effect of international competition on firm productivity and market power". In: *Oxford Handbook of Productivity*. Ed. by E. Grifell-Tatjé, C. Knox Lovell, and R. C. Sickles. Oxford University Press. Chap. 14, 388–415.

De Loecker, J. and F. Warzynski. 2012. Markups and firm-level export status. *American Economic Review* 102(6): 2437–71.

Di Giovanni, J., A. A. Levchenko, and J. Zhang. 2014. The global welfare impact of China: Trade integration and technological change. *American Economic Journal: Macroeconomics* 6(3): 153–183.

Dobbelaere, S. and K. Kiyota. 2018. Labor market imperfections, markups and productivity in multinationals and exporters. *Labour Economics* 53: 198–212.

Dobbelaere, S. and R. I. Luttens. 2016. Gradual collective wage bargaining. *Labour Economics* 40: 37–42.

Dobbelaere, S. and J. Mairesse. 2013. Panel data estimates of the production function and product and labor market imperfections. *Journal of Applied Econometrics* 28(1): 1–46.

Duan, W. and P. Martins. 2019. Rent sharing in China: Magnitude, heterogeneity and drivers. IZA Discussion Paper 12169. Institute of Labor Economics.

Gouriéroux, C., A. Holly, and A. Monfort. 1981. Kuhn-Tucker, likelihood ratio and Wald tests for nonlinear models with inequality constraints on the parameters. *Journal of Econometrics* 16(1): 166–.

— 1982. Likelihood ratio test, Wald test, and Kuhn-Tucker test in linear models with inequality constraints on the regression parameters. *Econometrica* 50(1): 63–80.

Hall, R. E. 1988. The relation between price and marginal cost in U.S. industry. *Journal of Political Economy* 96(5): 921–947.

Helpman, E. 2006. Trade, FDI, and the organization of firms. *Journal of Economic Literature* 44(3): 589–630.

Hsieh, C.-T. and P. J. Klenow. 2009. Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics* 124(4): 1403.

Kamal, F. and M. E. Lovely. 2012. Labor allocation in China: Implicit taxation of the heterogeneous non-state sector. *CESifo Economic Studies* 59(4): 731–758.

Kamal, F., M. E. Lovely, and D. Mitra. 2015. "Trade liberalization and labor shares in China". Mimeo.

Kikkawa, K., G. Magerman, and E. Dhyne. 2019. Imperfect competition in firm-to-firm trade. Working Paper 363. National Bank of Belgium.

Kodde, D. A. and F. C. Palm. 1984. "Testing equality and inequality restriction: A distance test". Mimeo.

— 1986. Wald criteria for jointly testing equality and inequality restrictions. *Econometrica* 54(5): 1243–1248.

Kudo, A. 1963. A multivariate analogue of the one-sided test. *Biometrika* 50(3/4): 403–418.

Lardy, N. R. 2004. *Integrating China into the global economy*. Brookings Institution Press.

Levinsohn, J. and M. Melitz. 2002. "Productivity in a differentiated products market equilibrium". Mimeo.

Lu, Y., Z. Tao, and Y. Wang. 2010. Union effects on performance and employment relations: Evidence from China. *China Economic Review* 21(1): 202–210.

Lu, Y. and L. Yu. 2015. Trade liberalization and markup dispersion: Evidence from China's WTO accession. *American Economic Journal: Applied Economics* 7(4): 221–53.

Maddison, A. 2007. *Chinese economic performance in the long run*. OECD.

Manning, A. 2003. *Monopsony in motion: Imperfect competition in labor markets*. Princeton University Press.

— 2011. "Imperfect competition in the labor market". In: *Handbook of Labor Economics*. Ed. by D. Card and O. Ashenfelter. Vol. 4B. Elsevier, 973–1041.

McDonald, I. M. and R. M. Solow. 1981. Wage Bargaining and Employment. *American Economic Review* 71(5): 896–908.

Morlacco, M. 2019. "Market power in input markets: Theory and evidence from French manufacturing". Mimeo.

Nickell, S. J. and M. Andrews. 1983. Unions, real wages and employment in Britain 1951-79. *Oxford Economic Papers* 35: 183–206.

Nüesch, P. E. 1964. "Multivariate tests of location for restricted alternatives". ETH Zürich, PhD thesis.

— 1966. On the problem of tsting location in multivariate populations for restricted alternatives. *The Annals of Mathematical Statistics* 37(1): 113–119.

Perkins, D. H. and T. G. Rawski. 2008. "Forecasting China's economic growth to 2025". In: *China's Great Economic Transformation*. Ed. by L. Brandt and T. G. Rawski. Cambridge University Press, 829–886.

Perlman, M. D. 1969. One-sided testing problems in multivariate analysis. *The Annals of Mathematical Statistics* 40(2): 549–567.

Robertson, T. and F. T. Wright. 1983. On approximation of the level probabilities and associated distributions in order restricted inference. *Biometrika* 70(3): 597–606.

Robertson, T., F. Wright, and R. Dykstra. 1988. *Order restricted statistical inference*. Wiley, New York.

Shapiro, A. 1988. Towards a unified theory of inequality constrained testing in multivariate analysis. *International Statistical Review / Revue Internationale de Statistique* 56(1): 49–62.

Shapiro, A. 1985. Asymptotic distribution of test statistics in the analysis of moment structures under inequality constraints. *Biometrika* 72(1): 133–144.

Silvapulle, M. J. 1996. On an F-type statistic for testing one-sided hypotheses and computation of chi-bar-squared weights. *Statistics & Probability Letters* 28(2): 137–141.

Silvapulle, M. J. and P. K. Sen. 2011. *Constrained statistical inference: Order, inequality, and shape constraints*. Vol. 912. John Wiley & Sons.

Siskind, V. 1976. Approximate probability integrals and critical values for Bartholomew's test for ordered means. *Biometrika* 63(3): 647–654.

Stole, L. A. and J. Zwiebel. 1996. Intra-firm bargaining under non-binding contracts. *Review of Economic Studies* 63(3): 375–410.

Tybout, J. R. 2008. "Plant- and firm-Level evidence on "new" trade theories". In: *Handbook of International Trade*. Ed. by E. Choi and J. Harrigan. Wiley-Blackwell. Chap. 13, 388–415.

Wolak, F. A. 1987. An exact test for multiple inequality and equality constraints in the linear regression model. *Journal of the American Statistical Association* 82(399): 782–793.

Wolfe, P. 1959. The simplex method for quadraticprogramming. *Econometrica* 27(3): 382–398.

World Bank and the Development Research Center of the State Council, P.R. China. 2013. *China 2030: Building a Modern, Harmonious, and Creative Society*. The World Bank.

Zhu, X. 2012. Understanding China's growth: Past, present, and future. *Journal of Economic Perspectives* 26(4): 103–24.

Table 1: Regimes of competitiveness

Regime R	$LMS = WMD$: $\psi_{it} < 0$	$LMS = WMP$: $\psi_{it} = 0$	$LMS = WMU$: $\psi_{it} > 0$
$PMS = PMC$: $\mu_{it} - 1 = 0$	*PMC-WMD*	*PMC-WMP*	*PMC-WMU*
$PMS = PMU$: $\mu_{it} - 1 > 0$	*PMU-WMD*	*PMU-WMP*	*PMU-WMU*

Table 2: Classification procedure of firm-year regimes of competitiveness

$R = PMC\text{-}WMD$		
$H_{01}:\ \mu_{it} - 1 = 0$	against	$H_{11}:\ \mu_{it} - 1 \neq 0$
$H_{02}:\ \psi_{it} < 0$	against	$H_{12}:\ \psi_{it} \nless 0$
$R = PMU\text{-}WMD$		
$H_{01}:\ \mu_{it} - 1 > 0$	against	$H_{11}:\ \mu_{it} - 1 \ngtr 0$
$H_{02}:\ \psi_{it} < 0$	against	$H_{12}:\ \psi_{it} \nless 0$
$R = PMC\text{-}WMP$		
$H_0:\ \mu_{it} - 1 = \psi_{it} = 0$	against	$H_1:\ \mu_{it} - 1 \neq \psi_{it} \neq 0$
$R = PMU\text{-}WMP$		
$H_{01}:\ \mu_{it} - 1 > 0$	against	$H_{11}:\ \mu_{it} - 1 \ngtr 0$
$H_{02}:\ \psi_{it} = 0$	against	$H_{12}:\ \psi_{it} \neq 0$
$R = PMC\text{-}WMU$		
$H_{01}:\ \mu_{it} - 1 = 0$	against	$H_{11}:\ \mu_{it} - 1 \neq 0$
$H_{02}:\ \psi_{it} > 0$	against	$H_{12}:\ \psi_{it} \ngtr 0$
$R = PMU\text{-}WMU$		
$H_{01}:\ \mu_{it} - 1 > 0$	against	$H_{11}:\ \mu_{it} - 1 \ngtr 0$
$H_{02}:\ \psi_{it} > 0$	against	$H_{12}:\ \psi_{it} \ngtr 0$

Table 3: Descriptive statistics

	Mean	Sd.	Q_1	Q_2	Q_3	# Obs.
Real firm output growth rate Δq_{it}	.118	.282	$-.046$	.105	.275	258,045
Labor growth rate Δn_{it}	.033	.213	$-.054$	0	.111	258,117
Materials growth rate Δm_{it}	.100	.307	$-.085$	.090	.277	258,112
Capital growth rate Δk_{it}	.054	.475	$-.105$	$-.016$	.151	257,203
$\alpha_{it}^N(\Delta n_{it} - \Delta k_{it}) + \alpha_{it}^M(\Delta m_{it} - \Delta k_{it})$	.032	.468	$-.144$	.054	.237	257,092
$\alpha_{it}^N(\Delta k_{it} - \Delta n_{it})$	.003	.083	$-.018$	$-.001$	.018	257,097
Solow Residual SR_{it}[a]	.031	.145	$-.041$	.029	.103	257,025
Labor share in total revenue α_{it}^N	.146	.106	.070	.121	.193	315,543
Material share in total revenue α_{it}^M	.771	.097	.721	.780	.832	315,694
Capital share in total revenue[b]	.083	.117	.012	.082	.156	315,543
Employment (FTEs)	365	1,279	80	152	324	315,694

Note: [a] $SR_{it} = \Delta q_{it} - \alpha_{it}^N \Delta n_{it} - \alpha_{it}^M \Delta m_{it} - (1 - \alpha_{it}^N - \alpha_{it}^M)\Delta k_{it}$,
[b] $1 - \alpha_{it}^N - \alpha_{it}^M$.

Table 4: Time variation in dominant regimes of competitiveness by industry

IND	Industry	2000	2001	2002	2003	2004	2005	2006
1	Food Proc.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
2	Food	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
3	Bev. & Tob.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
4	Text	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
5	Wear	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
6	Leather	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
7	Wood	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD
8	Furn.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMD	PMU-WMD	PMU-WMD
9	Paper	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
10	Print.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
11	Petrol	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
12	Chem.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
13	Pharma.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
14	Chem. Fiber	PMU-WMU	PMU-WMD	PMU-WMU	PMU-WMU	PMU-WMD	PMU-WMD	PMU-WMU
15	Rubber	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
16	Plastic	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
17	Minerals	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
18	Fer. Metal	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
19	Nonfer. Metal	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD	PMU-WMD
20	Fab. Metal	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
21	Gen. Mach.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
22	Spec. Mach.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
23	Transport	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
24	Elec. Mach.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
25	Comp.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
26	Instr.	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
27	Educ. & Sport	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU
28	NEC	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU	PMU-WMU

Table 5: Prevailing regimes of competitiveness at the industry level

IND	Industry	*PMC-WMD*	*PMU-WMD*	*PMC-WMP*	*PMU-WMP*	*PMC-WMU*	*PMU-WMU*	Dominant Regime
9	Paper	0.02	0.06	0.01	0.10	0.67	0.99	*PMU-WMU*
10	Print.	0.02	0.05	0.02	0.06	0.48	0.99	*PMU-WMU*
15	Rubber	0.04	0.20	0.03	0.32	0.89	0.99	*PMU-WMU*
21	Gen. Mach.	0.02	0.02	0.01	0.02	0.16	0.98	*PMU-WMU*
2	Food	0.05	0.09	0.02	0.09	0.66	0.96	*PMU-WMU*
5	Wear	0.03	0.03	0.02	0.04	0.16	0.96	*PMU-WMU*
17	Minerals	0.03	0.09	0.01	0.08	0.28	0.95	*PMU-WMU*
25	Comp.	0.01	0.03	0.00	0.05	0.53	0.95	*PMU-WMU*
27	Educ. & Sport	0.07	0.18	0.02	0.20	0.63	0.95	*PMU-WMU*
22	Spec. Mach.	0.05	0.07	0.01	0.04	0.43	0.94	*PMU-WMU*
16	Plastic	0.05	0.10	0.01	0.08	0.40	0.90	*PMU-WMU*
18	Fer. Metal	0.11	0.34	0.01	0.31	0.89	0.90	*PMU-WMU*
11	Petrol	0.13	0.59	0.01	0.55	0.77	0.88	*PMU-WMU*
4	Text	0.12	0.22	0.02	0.14	0.22	0.87	*PMU-WMU*
20	Fab. Metal	0.12	0.24	0.02	0.16	0.39	0.87	*PMU-WMU*
6	Leather	0.18	0.30	0.05	0.21	0.47	0.86	*PMU-WMU*
23	Transport	0.12	0.16	0.01	0.07	0.40	0.81	*PMU-WMU*
28	NEC	0.11	0.20	0.02	0.16	0.46	0.81	*PMU-WMU*
12	Chem.	0.15	0.22	0.01	0.10	0.50	0.80	*PMU-WMU*
13	Pharma.	0.25	0.42	0.04	0.25	0.33	0.76	*PMU-WMU*
14	Chem. Fiber	0.32	0.68	0.09	0.57	0.73	0.76	*PMU-WMU*
1	Food Proc.	0.27	0.47	0.03	0.30	0.49	0.75	*PMU-WMU*
24	Elec. Mach.	0.14	0.25	0.02	0.16	0.44	0.75	*PMU-WMU*
3	Bev. & Tob.	0.30	0.51	0.03	0.30	0.47	0.72	*PMU-WMU*
26	Instr.	0.40	0.49	0.08	0.19	0.47	0.66	*PMU-WMU*
7	Wood	0.57	0.70	0.06	0.23	0.42	0.46	*PMU-WMD*
19	Nonfer. Metal	0.51	0.62	0.02	0.15	0.28	0.42	*PMU-WMD*
8	Furn.	0.46	0.58	0.06	0.22	0.45	0.58	*PMU-WMD*

The weighted frequencies of occurrence of each regime at the industry level are shown, as well as the dominant regime on the basis of the highest weighted frequency of occurrence. The weights are based on the share of value added of each firm within the industry.

Table 6: WTO entry effect on regimes of competitiveness at the industry level

IND	Industry	*PMC-WMD*	*PMU-WMD*	*PMC-WMP*	*PMU-WMP*	*PMC-WMU*	*PMU-WMU*
1	Food Proc.	−0.13	−0.05	−0.08	−0.01	0.00	-
2	Food	−0.05	−0.05	−0.02	0.00	−0.04	-
3	Bev. & Tob.	−0.33*	−0.17‡	−0.15	−0.03	−0.08	-
4	Text	−0.01	−0.01	−0.01	0.00	0.00	-
5	Wear	0.02	0.01	0.02	0.00	−0.09	-
6	Leather	−0.04	0.01	−0.02	0.04	0.00	-
8	Furn.	0.25*,†	0.29*,†,◇	0.13	0.14	0.04	-
9	Paper	−0.01	−0.02	0.00	0.00	0.09	-
10	Print.	0.00	0.01	0.00	−0.02	0.00	-
11	Petrol	0.06	0.06	0.03	−0.04	−0.15‡	-
12	Chem.	0.15	0.13	0.08	0.07	0.13	-
13	Pharma.	0.01	0.01	0.02	0.01	0.01	-
14	Chem. Fiber	0.01	0.08†	0.01	0.02	−0.03	-
15	Rubber	0.01	0.03	0.00	0.10	0.04†	-
16	Plastic	−0.01	0.00	−0.02	0.00	0.08	-
17	Minerals	0.01	−0.01	0.01	0.00	−0.02	-
18	Fer. Metal	0.10	0.30*	0.05	0.29*	0.02	-
20	Fab. Metal	−0.07	−0.08	−0.02	−0.02	0.01	-
21	Gen. Mach.	0.00	0.00	0.00	0.00	−0.01	-
22	Spec. Mach.	0.11	0.10	0.07	0.05	0.07	-
23	Transport	0.14	0.14	0.10	0.09	0.14	-
24	Elec. Mach.	0.05	−0.01	0.00	−0.05	0.04	-
25	Comp.	0.05	0.04	0.05	0.04	−0.01	-
26	Instr.	0.11	0.12	0.09	0.10	0.03	-
27	Educ. & Sport	−0.06	−0.01	−0.03	0.03	0.06	-
28	NEC	−0.05	−0.06	−0.06	−0.10	−0.04	-
7	Wood	−0.02	-	0.01	0.00	−0.01	−0.02
19	Nonfer. Metal	0.02	-	−0.02	−0.03	−0.11	−0.08

* denotes a regime that displays a difference-in-differences change exceeding 25 percentage points in absolute value. † denotes a regime that is more than 10 percentage points apart from the pre-WTO dominant regime prior to WTO entry and less than 10 percentage points apart after WTO entry. ‡ denotes a regime that is less than 10 percentage points apart from the pre-WTO dominant regime prior to WTO entry and more than 10 percentage points apart after WTO entry. ◇ denotes a regime that has become the dominant regime in the post-WTO period.

Table 7: WTO impact on switching away from an imperfectly competitive product/labor market setting in the pre-WTO period

	$\mathbb{P}(PMU\text{-switch} \mid \boldsymbol{x})$			$\mathbb{P}(WMD\text{-switch} \mid \boldsymbol{x})$			$\mathbb{P}(WMU\text{-switch} \mid \boldsymbol{x})$		
	Probit	OLS	IV	Probit	OLS	IV	Probit	OLS	IV
Input tariff$_{t-1}$	.002	.003	.003	.203**	.238**	.267***	.032**	.041**	.038*
	(.002)	(.002)	(.002)	(.095)	(.096)	(.098)	(.015)	(.021)	(.020)
Output tariff$_{t-1}$	-.000	-.000	-.000	-.089***	-.079***	-.090***	-.006	-.007*	-.007*
	(.000)	(.000)	(.000)	(.033)	(.025)	(.025)	(.004)	(.004)	(.004)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,223	84,223	84,223	6,440	6,440	6,440	112,186	112,186	112,186

Standard errors in parentheses are clustered at the 4-digit industry-year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Probit, OLS, and IV estimates of the impact of WTO entry on the prevalence of product/labor market power at the firm level, that is, on the probability of switching away from setting price-cost markups (PMU-switch), setting wage markdowns (WMD-switch), or paying wage markups (WMU-switch). The impact of trade liberalization is captured by 1-year lagged input and output tariffs at the industry level.

Table 8: WTO impact on the intensity of firms' product/labor market power

	$\ln \widehat{\mu} \| PMU$		$\ln(\widehat{\varepsilon}^{N}_{W}) \| WMD$		$\ln\left(\frac{\widehat{\phi}}{1-\widehat{\phi}}\right) \| WMU$	
	OLS	IV	OLS	IV	OLS	IV
Input tariff$_{t-1}$	-.716**	-.780*	-7.706***	-7.498***	-4.376*	-4.437
	(.310)	(.422)	(2.248)	(2.386)	(2.356)	(3.084)
Output tariff$_{t-1}$	.172	.116	.225	-.115	-.718	-.176
	(.156)	(.132)	(.794)	(.842)	(.805)	(.714)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Inverse Mills ratio	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	.034	.033	.038	.037	.025	.024
Observations	153,368	153,368	19,151	19,151	170,288	170,288

Standard errors in parentheses are clustered at the 4-digit industry-year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

OLS and IV estimates of the impact of WTO entry on the intensity of firms' product/labor market power conditional on the relevant product/labor market setting. Columns 1 and 2 estimate the impact of WTO entry on the level of a firm's price-cost markup for firms classified as setting price-cost markups ($PMS = PMU$). Columns 3 and 4 estimate the impact of WTO entry on the level of a firm's labor supply elasticity for firms classified as setting wage markdowns ($LMS = WMD$). Columns 5 and 6 estimate the impact of WTO entry on the level of workers' bargaining power for firms classified as paying wage markups ($LMS = WMU$). The impact of trade liberalization is captured by 1-year lagged input and output tariffs at the industry level.

Table 9: Disentangling trade liberalization and compositional effects

	$\ln\widehat{\mu}\lvert PMU$-stay		$\ln(\widehat{\varepsilon}^N_W)\lvert\, WMD$-stay		$\ln\left(\frac{\widehat{\phi}}{1-\widehat{\phi}}\right)\lvert\, WMU$-stay	
	OLS	IV	OLS	IV	OLS	IV
Input tariff$_{t-1}$	-.675**	-.658	-7.587***	-7.620***	-2.838	-2.758
	(.303)	(.422)	(1.679)	(1.692)	(1.813)	(2.278)
Output tariff$_{t-1}$	-.009	-.016	.227	-.130	-.052	.109
	(.108)	(.113)	(.635)	(.585)	(.475)	(.550)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	.040	.040	.058	.057	.021	.021
Observations	84,197	84,197	5,815	5,815	91,076	91,076

Standard errors in parentheses are clustered at the 4-digit industry-year level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

OLS and IV estimates of the impact of WTO entry on the intensity of firms' product/labor market power conditional on being a stayer for the relevant product/labor market setting. Columns 1 and 2 estimate the impact of WTO entry on the level of a firm's price-cost markup for firms classified as setting price-cost markups ($PMS = PMU$) in both the pre- and post-WTO periods. Columns 3 and 4 estimate the impact of WTO entry on the level of a firm's labor supply elasticity for firms classified as setting wage markdowns ($LMS = WMD$) in both the pre- and post-WTO periods. Columns 5 and 6 estimate the impact of WTO entry on the level of workers' bargaining power for firms classified as paying wage markups ($LMS = WMU$) in both the pre- and post-WTO periods. The impact of trade liberalization is captured by 1-year lagged input and output tariffs at the industry level.

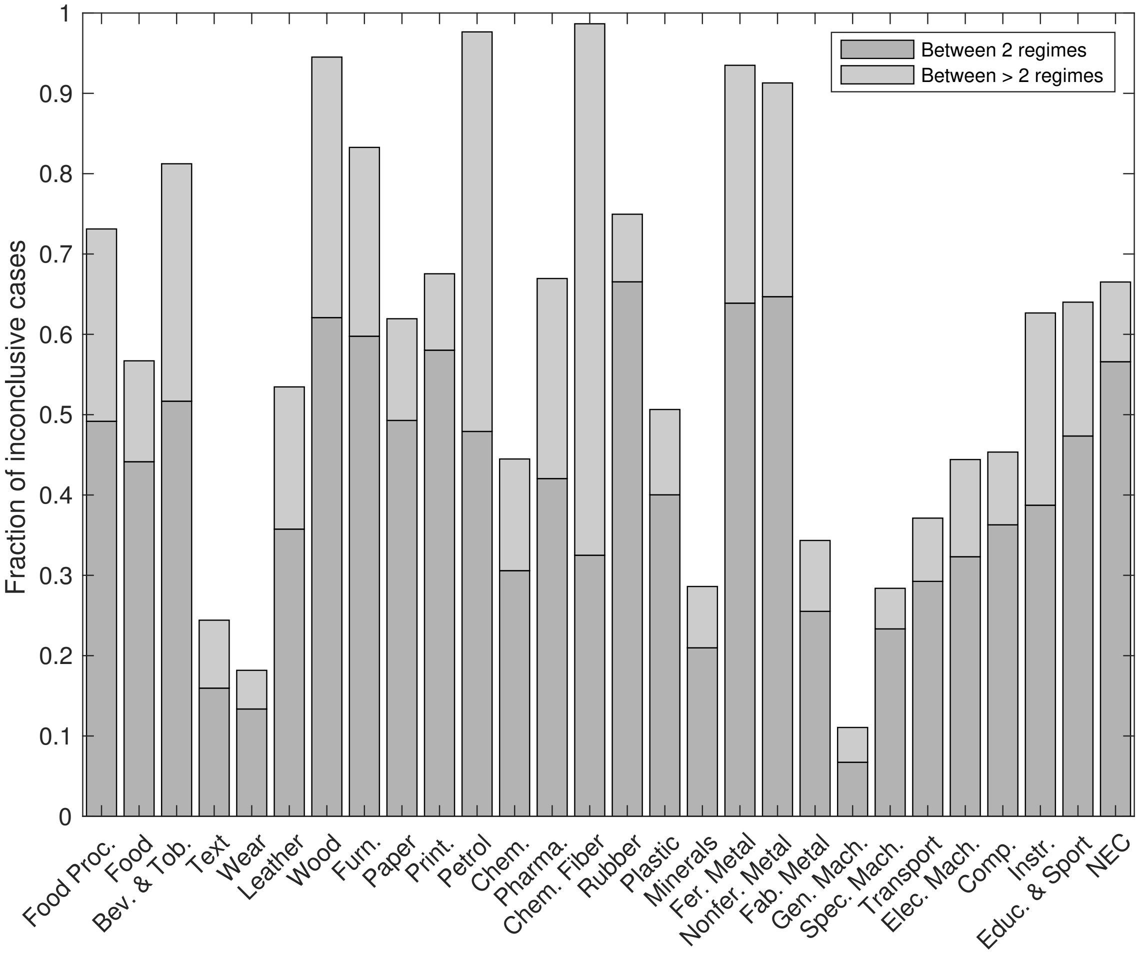
Table 10: Heterogeneous WTO impact on the intensity of firms' product/labor market power

	$\ln \widehat{\mu} \| WMD$		$\ln(\widehat{\varepsilon}_W^N) \| PMU$	
	OLS	IV	OLS	IV
Input tariff$_{t-1}$	-1.144*	-1.019	-19.011***	-17.292***
	(.656)	(.691)	(5.536)	(6.040)
Output tariff$_{t-1}$	-.147**	-.170***	2.700*	2.203
	(.065)	(.060)	(1.564)	(1.749)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Inverse Mills ratio	Yes	Yes	Yes	Yes
Adjusted-R^2	.112	.112	.107	.107
Observations	19,203	19,203	3,291	3,291

Standard errors in parentheses are clustered at the 4-digit industry-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

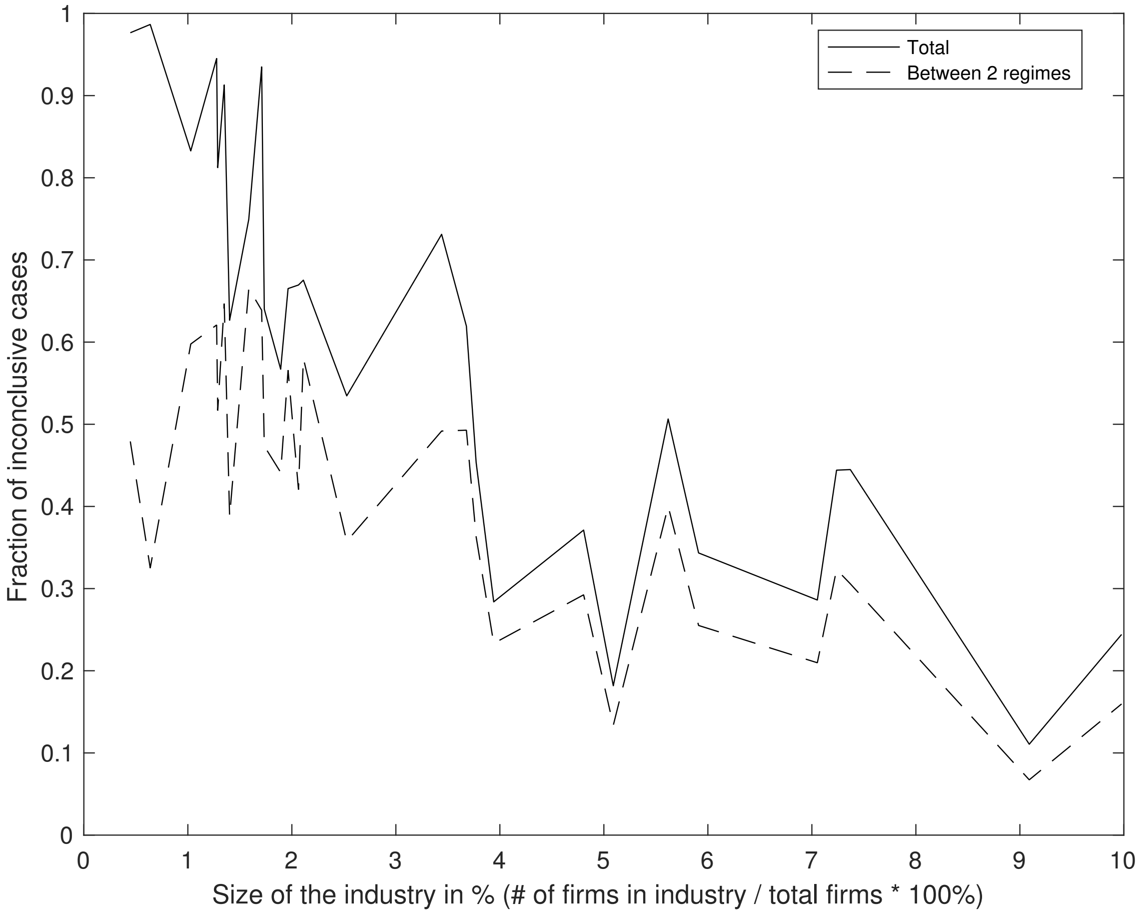
OLS and IV estimates of the impact of WTO entry on the intensity of firms' product/labor market power, conditional on the labor/product market setting. Columns 1 and 2 estimate the impact of WTO entry on the level of a firm's price-cost markup for firms exerting labor market power, that is, for firms classified as setting wage markdowns ($LMS = WMD$). Columns 3 and 4 estimate the impact of WTO entry on the level of a firm's labor supply elasticity for firms exerting product market power, that is, for firms classified as setting price-cost markups ($PMS = PMU$). The impact of trade liberalization is captured by 1-year lagged input and output tariffs at the industry level.

Figure 1: Composition of inconclusiveness at the industry level



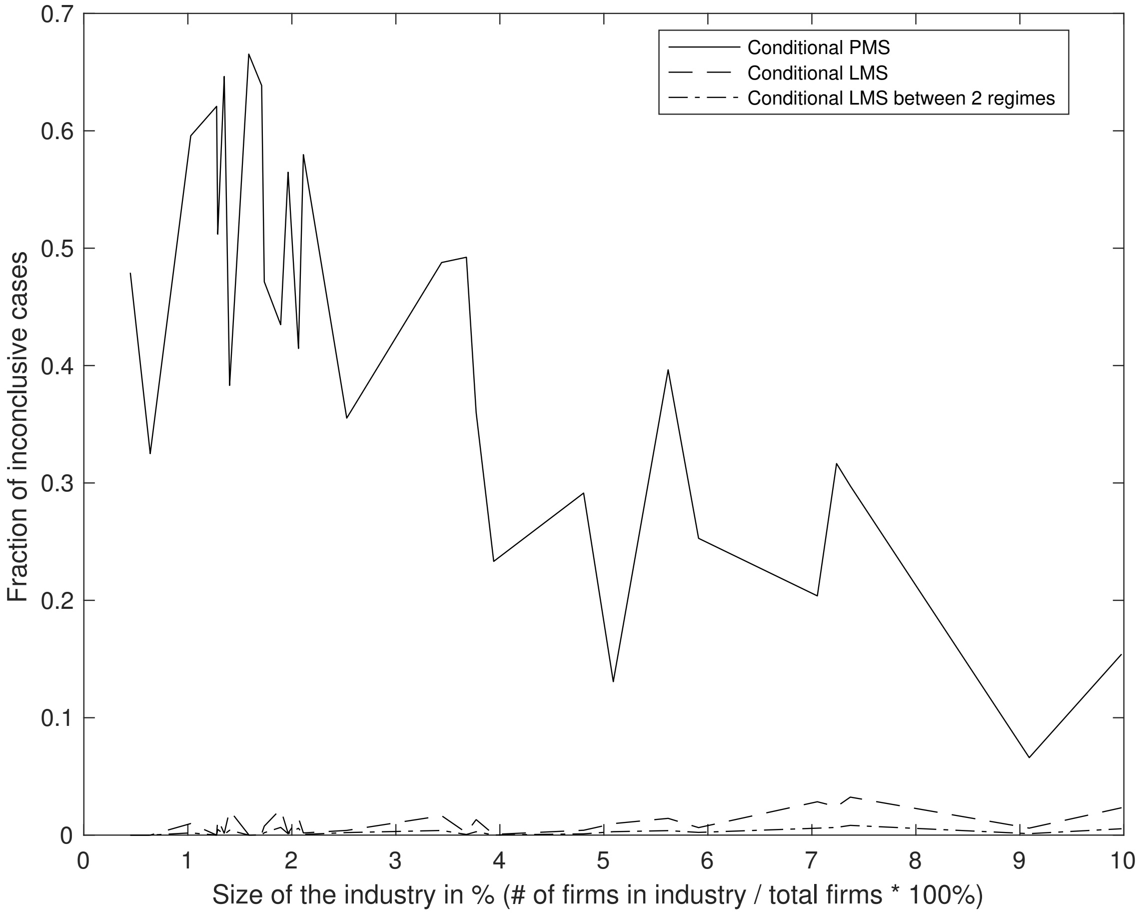
The composition of inconclusiveness at the industry level is shown in a bar graph. Inconclusiveness is split into to mild inconclusiveness (inconclusiveness between two regimes) and severe inconclusiveness (inconclusiveness between more than two regimes).

Figure 2: Relationship between inconclusiveness and industry size



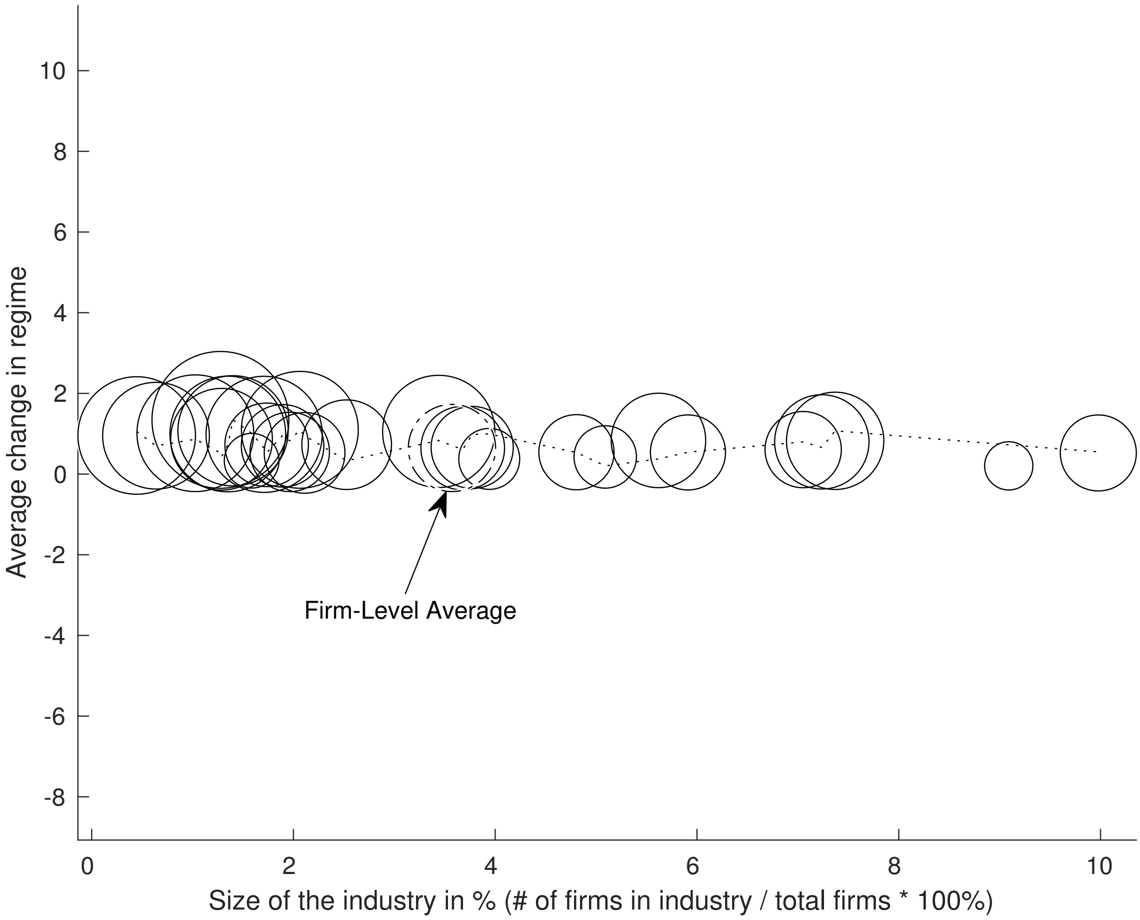
The relationship between inconclusiveness and industry size is shown for total inconclusiveness (solid line) as well as inconclusiveness between two regimes (dashed line).

Figure 3: Relationship between conditional inconclusiveness and industry size



The relationship between inconclusiveness and industry size is shown for conditional product market setting (*PMS*) inconclusiveness (solid line), conditional labor market setting (*LMS*) inconclusiveness (dashed line), and conditional *LMS* inconclusiveness between 2 regimes (dashed-dotted line). Conditional *PMS* (*LMS*) inconclusiveness is defined as inconclusiveness based on *PMS* (*LMS*), conditional on being able to identify the *LMS* (*PMS*).

Figure 4: Average change in regime of competitiveness at the industry level and within-industry variation



The average change in regime of competitiveness at the industry level is shown as the center of each circle. The average change is measured as the difference in regime between the first and last year available for each firm, then aggregated to the industry level. Variation in the change in regime of competitiveness, measured as the standard deviation, is visualized as the radius of each circle. The dashed circle denotes the firm-level average. Industries are ranked according to their size, which is measured as the fraction of the number of firms belonging to the industry.

Appendix A: Distance test

The distance test builds upon the earlier work of Nüesch (1964, 1966), Perlman (1969), and Gouriéroux *et al.* (1981, 1982). The latter propose the likelihood ratio, Kuhn-Tucker and Lagrange multiplier tests for nonlinear as well as linear models for hypothesis testing of the following form: $H_0: \ h(\boldsymbol{\theta}) = \mathbf{0}$, against $H_1: \ h(\boldsymbol{\theta}) > \mathbf{0}$. They show that the distribution of the different test statistics under the null is a weighted-χ^2 distribution. The main empirical difficulty related to this large-sample hypothesis testing is the derivation of the weights of the weighted-χ^2 distribution.

Let us introduce some notation in order to define the distance test in formal mathematical terms. Let $\boldsymbol{\theta}$ denote a $(p \times 1)$ vector of parameters of interest and let $h(\boldsymbol{\theta})$ be a continuous function denoting the restrictions on the parameters. Assume $\boldsymbol{\theta}$ can be consistently estimated by $\bar{\boldsymbol{\theta}}$. Let $\boldsymbol{\Omega}$ denote the variance-covariance matrix of $\boldsymbol{\theta}$, which can be consistently estimated by $\bar{\boldsymbol{\Omega}}$. Now, transform $\boldsymbol{\theta}$ and $\bar{\boldsymbol{\theta}}$ into new parameter vectors as follows (Kodde and Palm, 1984, 1986):

$$\boldsymbol{\gamma} = N^{\frac{1}{2}} h(\boldsymbol{\theta}) \qquad \text{and} \qquad \bar{\boldsymbol{\gamma}} = N^{\frac{1}{2}} h(\bar{\boldsymbol{\theta}}),$$

where N denotes the sample size.

The variance-covariance matrix of $\boldsymbol{\gamma}$ and $\bar{\boldsymbol{\gamma}}$ are

$$\boldsymbol{\Sigma} = \frac{\partial h(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}'} \boldsymbol{\Omega} \frac{\partial h(\boldsymbol{\theta})'}{\partial \boldsymbol{\theta}} \qquad \text{and} \qquad \bar{\boldsymbol{\Sigma}} = \frac{\partial h(\bar{\boldsymbol{\theta}})}{\partial \bar{\boldsymbol{\theta}}'} \bar{\boldsymbol{\Omega}} \frac{\partial h(\bar{\boldsymbol{\theta}})'}{\partial \bar{\boldsymbol{\theta}}}.$$

Finally, define the distance function in the metric of $\boldsymbol{\Sigma}$ of a vector $\boldsymbol{\mu}$ from the origin, as:

$$\|\boldsymbol{\mu}\| = \boldsymbol{\mu}' \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}.$$

Kodde and Palm (1984, 1986) distinguish five different equality and inequality restrictions, which all slightly alter the definition of the test. To implement our classification procedure, we only need the following three definitions of the test: (i) a standard test for zero under the null, (ii) a test for inequality restrictions under the null, and (iii) a test for equality and inequality restrictions under the null.

First, if the following equality restrictions are tested $H_0: \ \boldsymbol{\gamma} = \mathbf{0}$ against $H_1: \ \boldsymbol{\gamma} \neq \mathbf{0}$, the distance test becomes:

$$D = \|\bar{\boldsymbol{\gamma}}\|,$$

which is equivalent to the Wald test.

Second, the test of inequality restrictions under the null, $H_0\colon\ \boldsymbol{\gamma} \geqslant \mathbf{0}$ against $H_1\colon\ \boldsymbol{\gamma} \ngeqslant \mathbf{0}$, leads to the following test statistic:

$$D = \|\bar{\boldsymbol{\gamma}} - \tilde{\boldsymbol{\gamma}}\| \,,$$

where $\tilde{\boldsymbol{\gamma}}$ is the solution of

$$\min_{\boldsymbol{\gamma} \geqslant \mathbf{0}} \quad \|\bar{\boldsymbol{\gamma}} - \boldsymbol{\gamma}\| \,, \tag{A.1}$$

so the distance test equals the minimum of (A.1).

Third, if one is interested in testing the following hypothesis $H_0\colon\ \boldsymbol{\gamma}_1 = \mathbf{0},\ \boldsymbol{\gamma}_2 \geqslant \mathbf{0}$ against $H_1\colon\ \boldsymbol{\gamma}_1 \neq \mathbf{0},\ \boldsymbol{\gamma}_2 \ngeqslant \mathbf{0}$, the distance test takes the following form:

$$\begin{aligned} D = \|\bar{\boldsymbol{\gamma}} - \tilde{\boldsymbol{\gamma}}\| = {} & \left(\bar{\boldsymbol{\gamma}}_2 - \tilde{\boldsymbol{\gamma}}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right)' \left(\boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}\right)^{-1} \left(\bar{\boldsymbol{\gamma}}_2 - \tilde{\boldsymbol{\gamma}}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right) \\ & + \bar{\boldsymbol{\gamma}}_1'\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1 \,, \end{aligned}$$

where $\tilde{\boldsymbol{\gamma}}_2$ is the solution of the program:

$$\min_{\boldsymbol{\gamma}_2 \geqslant \mathbf{0}} \quad \left(\bar{\boldsymbol{\gamma}}_2 - \boldsymbol{\gamma}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right)' \left(\boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}\right)^{-1} \left(\bar{\boldsymbol{\gamma}}_2 - \boldsymbol{\gamma}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right) \,. \tag{A.2}$$

Eqs. (A.1) and (A.2) can be solved by standard quadratic programming techniques (see Beale, 1955; Wolfe, 1959).

Let us now discuss the distribution of the different forms of the distance test. As mentioned earlier, the distance test follows in general a weighted-χ^2 distribution but these distributions slightly differ across hypotheses. The different hypotheses and their respective distributions are discussed in the same order as above.

First, $H_0\colon\ \boldsymbol{\gamma} = \mathbf{0}$ against $H_1\colon\ \boldsymbol{\gamma} \neq \mathbf{0}$ boils down to the well-known Wald test, which is $\chi^2(p)$ distributed, with p degrees of freedom (the number of restrictions).

Second, for the problem of testing $H_0\colon\ \boldsymbol{\gamma} \geqslant \mathbf{0}$ against $H_1\colon\ \boldsymbol{\gamma} \ngeqslant \mathbf{0}$, the distribution of D under H_0 is given by

$$\mathbb{P}\left(D \geqslant c \mid \boldsymbol{\Sigma}\right) = \sum_{i=0}^{p} \mathbb{P}(\chi^2(p-i) \geqslant c)\; w(p, i, \boldsymbol{\Sigma}) \,,$$

where $w(p, i, \boldsymbol{\Sigma})$ denotes the probability that i of the p elements of $\tilde{\boldsymbol{\gamma}}$ are strictly positive.

Third, for the problem of $H_0\colon\ \boldsymbol{\gamma}_1 = \mathbf{0},\ \boldsymbol{\gamma}_2 \geqslant \mathbf{0}$ against $H_1\colon\ \boldsymbol{\gamma}_1 \neq \mathbf{0},\ \boldsymbol{\gamma}_2 \ngeqslant \mathbf{0}$, the test statistic follows the distribution

$$\mathbb{P}\left(D \geqslant c \mid \boldsymbol{\Sigma}\right) = \sum_{i=0}^{p-q} \mathbb{P}(\chi^2(p-i) \geqslant c)\; w(p-q, i, \boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}) \,,$$

where $w(p-q, i, \mathbf{\Sigma}_{22}-\mathbf{\Sigma}_{21}\mathbf{\Sigma}_{11}^{-1}\mathbf{\Sigma}_{12})$ denotes the probability that i of the $p-q$ elements of $\tilde{\boldsymbol{\gamma}}_2$ are strictly positive, with q the number of equality restrictions and the variance-covariance matrix set equal to the conditional variance-covariance matrix of $\bar{\boldsymbol{\gamma}}_2$ given $\bar{\boldsymbol{\gamma}}_1$.

A.1. Weights in the distribution of the distance test

The weights in the weighted-χ^2 distribution are the probability content of obtaining a fixed number of positive elements in the solution of the quadratic programming problems. Since the quadratic programming problems differ across hypotheses, so do the weights w. The weights w are a function of (*i*) m the number of elements of $\boldsymbol{\xi}$, (*ii*) k the number of strictly positive values of $\boldsymbol{\xi}$, and (*iii*) $\mathbf{\Delta}$ the variance-covariance matrix of $\boldsymbol{\xi}$, such that $w(m, k, \mathbf{\Delta})$. Here $\boldsymbol{\xi}$ denotes the solution to one of the quadratic programming problems (A.1) or (A.2), i.e. $\tilde{\boldsymbol{\gamma}}$ or $\tilde{\boldsymbol{\gamma}}_2$, depending on the hypothesis. The number of combinations of zero and strictly positive values of $\boldsymbol{\xi}$ is 2^m, so it scales exponentially in the number of components of $\boldsymbol{\xi}$.

Different methods to determine the weights are present in the literature of inequality constraint testing. These different methods consist of (*i*) closed-form solutions, (*ii*) numerical approximation algorithms, (*iii*) Monte Carlo simulation techniques, (*iv*) upper and lower bound approximations, (*v*) statistical properties, and (*vi*) binomial distribution approximation. Closed-form solutions are derived by Kudo (1963), Shapiro (1985), Wolak (1987), and Shapiro (1988). Since the determination of closed-form solutions of the weights can be complex for a large number of elements m, multiple approximation approaches are developed. Numerical approximation methods are given by Siskind (1976), Bohrer and Chow (1978), Robertson and Wright (1983), and Robertson *et al.* (1988). Monte Carlo simulation techniques are proposed by Gouriéroux *et al.* (1982), Wolak (1987), Silvapulle (1996), Dardanoni and Forcina (1998), and Silvapulle and Sen (2011). The upper and lower bound approximation of Kodde and Palm (1984, 1986) circumvents the problem of determining the weights by approximating the critical values directly. In addition to the upper and lower bound approximation, Kodde and Palm (1984, 1986) derive a method to determine the weights using their statistical properties. Gouriéroux *et al.* (1982) propose the binomial distribution approximation to be a simple and fast approximation technique.

The general method of Kodde and Palm (1984, 1986) for calculating the weights can be used for cases $m \geqslant 4$, but entails the disadvantage that it scales exponentially in the number of components of $\boldsymbol{\xi}$. Monte Carlo simulation techniques may provide a solution as they do not have the caveat of scaling exponentially in m but such techniques do not produce exact weights. The binomial approximation of Gouriéroux *et al.* (1982) greatly reduces the numerical problems of obtaining the weights. Lower and upper bounds (Kodde and Palm, 1984, 1986) may not be sufficient for every real-world application and are therefore not considered. In this paper, we focus on computing the exact weights, as m stays relatively small.[22]

[22]A simulation study was performed to assess the performance of different approximation methods, namely (i) a Monte Carlo simulation technique and (ii) a binomial approximation. The objective of such comparison is to identify robustness and reliability of the approximation methods. This serves the purpose of encouraging the empirical applicability of the distance test, as it has a wide usage in applied economic research. We find that both approximation methods provide adequate to very accurate approximations of the true weights, while being computationally less demanding compared to computing the exact weights (results not reported but available upon request).

Appendix B: Additional tables and figures

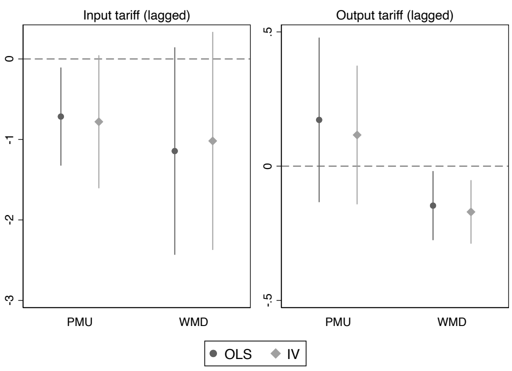
Table B.1: Panel structure

# of Participations[a]	# Obs.	%	# Firms	%
4	82,536	26.14	20,634	35.84
5	67,720	21.45	13,544	23.52
6	52,476	16.62	8,746	15.19
7	29,834	9.45	4,262	7.40
8	83,128	26.33	10,391	18.05
Total	315,694	100.00	57,577	100.00

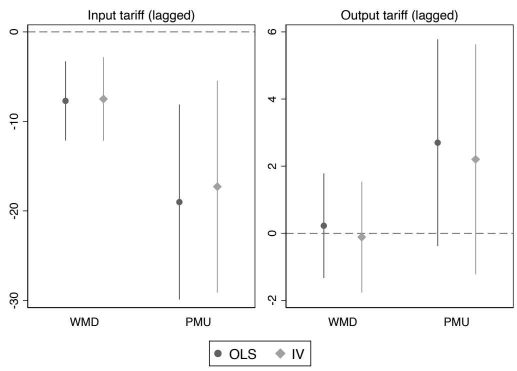
Note: [a]Median number of observations per firm: 5.

Figure B.1: Heterogeneous WTO impact on the intensity of firms' product/labor market power: OLS and IV estimates

(A) $\ln \hat{\mu}$



(B) $\ln \hat{\epsilon}^N_W$



Panel (A) shows estimated trade liberalization effects via input tariff (left) and output tariff (right) reductions on a firm's price-cost markup. Likewise, panel (B) shows estimated trade liberalization effects via input tariff (left) and output tariff (right) reductions on a firm's labor supply elasticity. The horizontal axis indicates the conditioning set for each estimated effect: *PMU* refers to the set of firms classified as setting price-cost markups (exerting product market power) and *WMD* refers to the set of firms setting wage markdowns (exerting labor market power).

Table B.2: Industry composition

IND	Industry	# Firms	# Obs
1	Food Proc.	2,059	10,959
2	Food	1,080	5,989
3	Bev. & Tob.	714	4,034
4	Textile	5,861	31,572
5	Wear	3,037	16,176
6	Leather	1,529	8,055
7	Wood	804	4,167
8	Furniture	635	3,298
9	Paper	2,085	11,577
10	Printing	1,158	6,630
11	Petroleum	256	1,419
12	Chemicals	4,091	23,103
13	Pharma.	1,123	6,449
14	Chem. Fibres	371	2,012
15	Rubber	886	4,968
16	Plastic	3,247	17,744
17	Minerals	4,090	22,299
18	Fer. Metal	994	5,408
19	Nonfer. Metal	783	4,272
20	Fab. Metal	3,441	18,683
21	Gen. Mach.	5,115	28,531
22	Spec. Mach.	2,275	12,432
23	Transport.	2,713	15,104
24	Elec. Mach.	4,090	22,740
25	Computing	2,146	11,903
26	Meas. Instr.	811	4,432
27	Educ. & Sport	996	5,470
28	NEC[a]	1,187	6,268
Total		57,577	315,694

Note: [a]Not elsewhere classified.

Table B.3: Average change in regime of competitiveness at the industry level and within-industry variation

IND	Industry	Size	Average Change	Variation (sd)
1	Food Proc.	8.60	1.06	1.39
2	Food	4.73	0.70	1.02
3	Bev. & Tob.	3.22	0.86	1.26
4	Text	24.95	0.52	0.94
5	Wear	12.73	0.42	0.77
6	Leather	6.32	0.73	1.11
7	Wood	3.19	1.34	1.70
8	Furn.	2.57	1.01	1.45
9	Paper	9.20	0.64	1.04
10	Print.	5.28	0.53	1.00
11	Petrol	1.12	0.96	1.46
12	Chem.	18.42	0.82	1.21
13	Pharma.	5.16	1.10	1.45
14	Chem. Fiber	1.60	0.95	1.32
15	Rubber	3.96	0.33	0.68
16	Plastic	14.05	0.83	1.17
17	Minerals	17.63	0.61	0.94
18	Fer. Metal	4.27	0.98	1.44
19	Nonfer. Metal	3.37	0.99	1.43
20	Fab. Metal	14.78	0.54	0.93
21	Gen. Mach.	22.73	0.20	0.60
22	Spec. Mach.	9.85	0.38	0.75
23	Transport	12.01	0.54	0.93
24	Elec. Mach.	18.09	0.80	1.17
25	Comp.	9.43	0.66	1.02
26	Instr.	3.50	1.07	1.37
27	Educ. & Sport	4.34	0.72	1.03
28	NEC	4.91	0.55	0.98
Firm-level avg.		8.93	0.65	1.08

This table shows the underlying numbers of Figure 4. For each of the 28 industries, it reports the number of average changes in regime of competitiveness and within-industry variation (standard deviation) of the average change. The size of each industry is defined as the fraction of the number of firms operating in each particular industry.

Table B.4: WTO impact on the intensity of labor market power of SOEs

	$\ln(\widehat{\varepsilon}_W^N)$|SOE		$\ln(\widehat{\varepsilon}_W^N)$|SOE $\cap$ *WMD*	
	OLS	IV	OLS	IV
Input tariff$_{t-1}$	-13.059***	-12.775***	-10.630***	-11.405***
	(3.319)	(3.467)	(3.855)	(3.990)
Output tariff$_{t-1}$	1.234	.709	.400	.234
	(1.171)	(1.082)	(1.411)	(1.532)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted-R^2	.059	.059	.089	.088
Observations	11039	11039	7791	7791

Standard errors in parentheses are clustered at the 4-digit industry-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

OLS and IV estimates of the impact of WTO entry on the intensity of labor market power of state-owned enterprises (SOEs). Columns 1 and 2 estimate the impact of WTO entry on the level of the labor supply elasticity of an SOE. Columns 3 and 4 estimate the impact of WTO entry on the level of the labor supply elasticity of an SOE that is classified as setting wage markdowns ($LMS = WMD$). The impact of trade liberalization is captured by 1-year lagged input and output tariffs at the industry level.

Table B.5: WTO impact on the intensity of firms' labor market power, conditional on switching away from setting wage markdowns in the pre-WTO period

	$\ln(\widehat{\varepsilon}_W^N)$| *WMD*-switch	
	OLS	IV
Input tariff$_{t-1}$	23.979*	26.858*
	(13.615)	(14.098)
Output tariff$_{t-1}$	-.311	-2.163
	(3.763)	(4.042)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Adjusted-R^2	.544	.543
Observations	212	212

Standard errors in parentheses are clustered at the 4-digit industry-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

OLS and IV estimates of the impact of WTO entry on the intensity of firms' labor market power, conditional on switching away from setting wage markdowns ($LMS = WMD$) in the pre-WTO period. The impact of trade liberalization is captured by 1-year lagged input and output tariffs at the industry level.

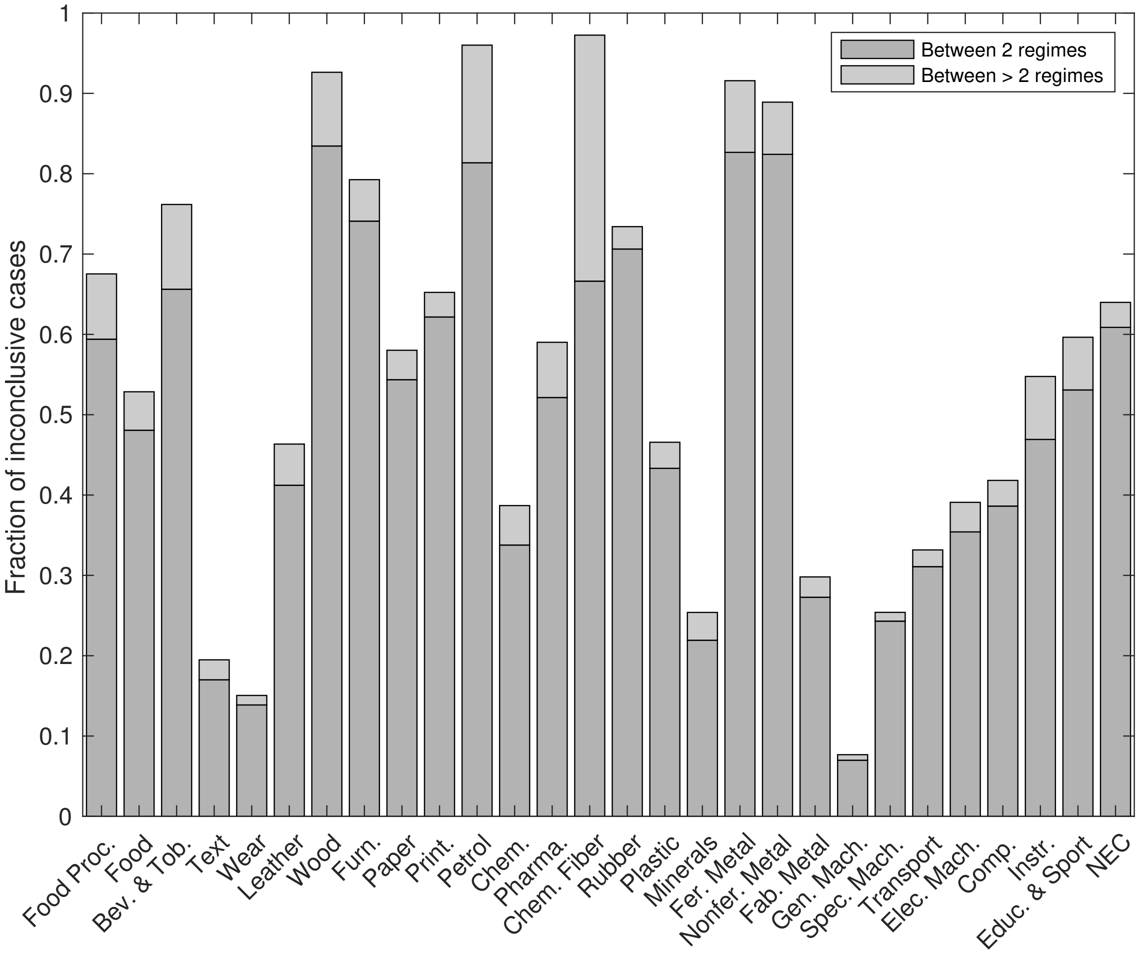
Table B.6: Disentangling heterogeneous trade liberalization and compositional effects

	$\ln\widehat{\mu}\vert WMD$-stay		$\ln(\widehat{\varepsilon}^N_W)\vert PMU$-stay	
	OLS	IV	OLS	IV
Input tariff$_{t-1}$	-1.523**	-1.417*	-5.520	-6.510
	(.723)	(.738)	(7.502)	(7.564)
Output tariff$_{t-1}$	-.360***	-.418***	2.774*	2.411
	(.128)	(.138)	(1.657)	(1.570)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted-R^2	.232	.231	.075	.074
Observations	5,843	5,843	1,610	1,610

Standard errors in parentheses are clustered at the 4-digit industry-year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

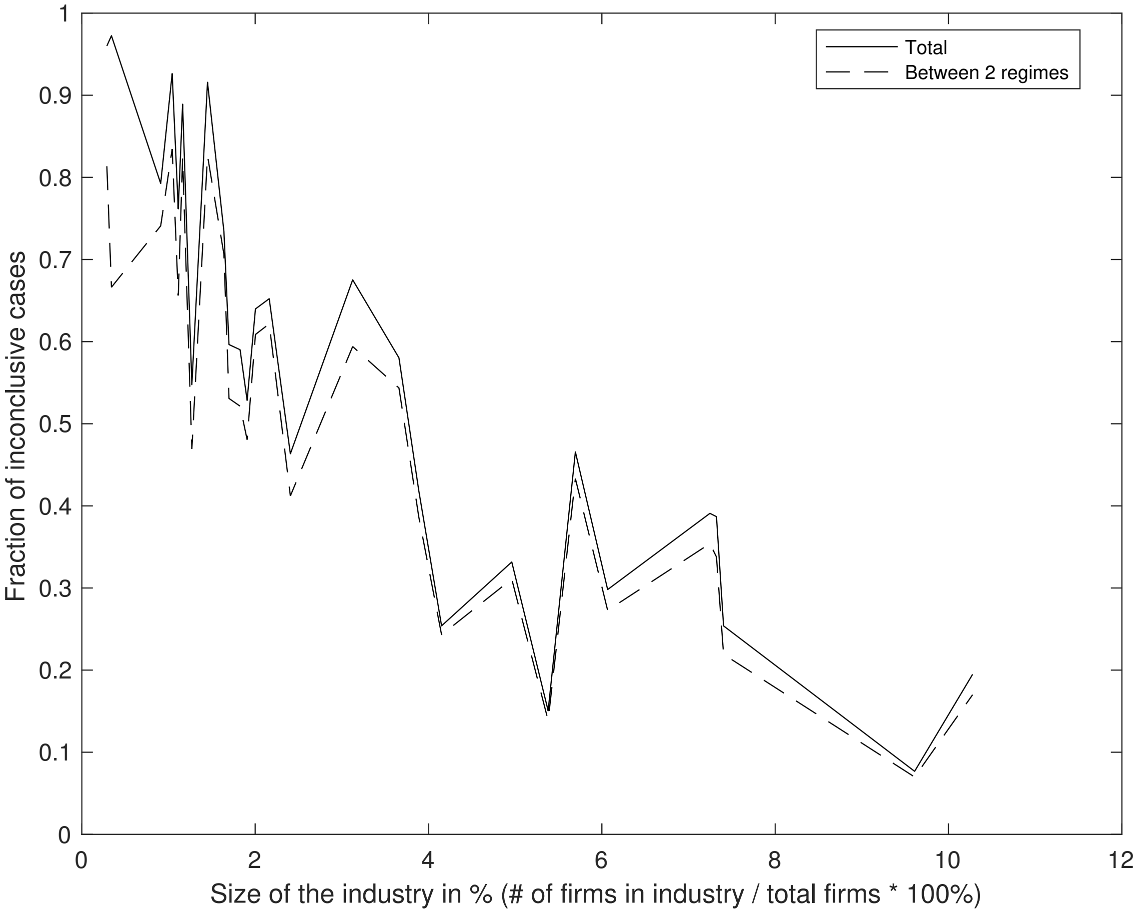
OLS and IV estimates of the impact of WTO entry on the intensity of firms' product/labor market power conditional on being a stayer for the labor/product market setting. Columns 1 and 2 estimate the impact of WTO entry on the level of a firm's price-cost markup for firms exerting labor market power, that is, for firms classified as setting wage markdowns ($LMS = WMD$) in both the pre- and post-WTO periods. Columns 3 and 4 estimate the impact of WTO entry on the level of a firm's labor supply elasticity for firms exerting product market power, that is, for firms classified as setting price-cost markups ($PMS = PMU$) in both the pre- and post-WTO periods. The impact of trade liberalization is captured by 1-year lagged input and output tariffs at the industry level.

Figure B.2: Composition of inconclusiveness at the industry level for subset of inconclusive cases between two or three regimes



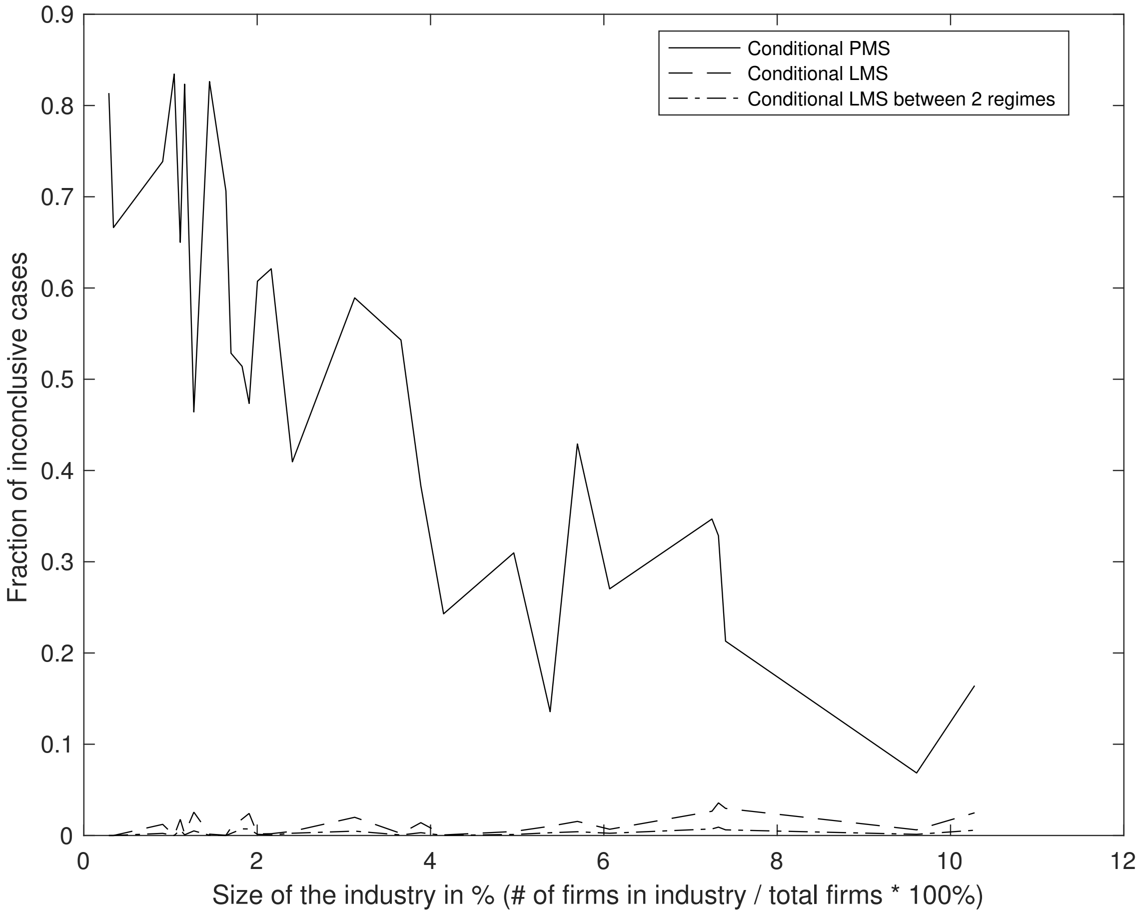
The composition of inconclusiveness at the industry level is shown in a bar graph for observations with inconclusiveness between two or three regimes. Inconclusiveness is split into mild inconclusiveness (inconclusiveness between two regimes) and severe inconclusiveness (inconclusiveness between more than two regimes).

Figure B.3: Relationship between inconclusiveness and industry size for subset of inconclusive cases between two or three regimes



The relationship between inconclusiveness and industry size is shown for total inconclusiveness (solid line) as well as inconclusiveness between two regimes (dashed line) for the subset of firm-year observations for which inconclusiveness is between two or three regimes.

Figure B.4: Relationship between conditional inconclusiveness and industry size for subset of inconclusive cases between two or three regimes



The relationship between inconclusiveness and industry size is shown for conditional product market setting (*PMS*) inconclusiveness (solid line), conditional labor market setting (*LMS*) inconclusiveness (dashed line), and conditional *LMS* inconclusiveness between 2 regimes (dashed-dotted line) for the subset of firm-year observations for which inconclusiveness is between two or three regimes. Conditional *PMS* (*LMS*) inconclusiveness is defined as inconclusiveness based on *PMS* (*LMS*), conditional on being able to identify the *LMS* (*PMS*).