Time variation in the competitiveness of product and labor markets of Chinese firms: An application of the distance test

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Abstract

This paper investigates potential shifts in Chinese firms' regimes characterizing the type of competition prevailing in product and labor markets in a period surrounding China's accession into the World Trade Organization (WTO) in 2001. To serve this purpose, we apply a procedure to test inequality restrictions, the distance test of Kodde and Palm (1984, 1986), and use an unbalanced panel of Chinese manufacturing firms covering the period 1999-2006. The dominant regimes of competitiveness in manufacturing industries are IC-MO (imperfect competition in the product market and monopsony in the labor market) and IC-EB (imperfect competition in the product market and efficient bargaining in the labor market). The dominant regime for a particular Chinese manufacturing industry is stable over time. This finding signals the prevalence of allocative inefficiencies in product and labor markets through distorting (factor) prices in Chinese industries. As such, we find no suggestive evidence for a decline of such inefficiencies after trade liberalization through WTO entry. This conclusion particularly holds for industries which consist of predominantly state-owned enterprises. To promote the empirical applicability of the distance test, we show that existing approximation methods (Monte Carlo simulation techniques and Binomial distribution) provide fairly accurate approximations of exact weights in the weighted-χ^2 distribution of the distance test, nullifying the burden of the computational complexity of determining these exact weights.

Keywords: Rent sharing, monopsony, price-cost mark-ups, trade liberalization, firm panel data, hypothesis testing, inequality restrictions, approximation.

JEL classification: C12, C23, C63, J30, L20, F61.

1. Introduction

Since the beginning of socio-economic reforms in 1978, China's transformation from a state socialist redistributive economy into an increasingly market-driven economy has reduced distortions, and led to substantial efficiency gains and rapid economic growth (Maddison, 1998; Fan et al., 2003). The role of market forces in domestic and international economic relations has become large by any standards, with the process of change having been accelerated by World Trade Organization (WTO) entry (OECD, 2005; Zhang and Tan, 2007; Holz, 2009).

China's transition from a planned allocation of labor in state-sector jobs to a labor market has been stimulated by economic globalization. Incentive mechanism and allocation system reforms, such as breaking up the iron rice-bowl in urban employment policy, eliminating a series of hukou-related institutional barriers deterring labor mobility and granting management power to determine wages within enterprises, have undoubtedly improved technical and allocative efficiencies (Cai et al., 2008). Yet, due to the partial, incremental and uneven nature of labor market reforms, numerous studies conclude that there is still significant segmentation in the labor market (Meng, 2000; Knight and Li, 2005; Zhang and Tan, 2007; Xie and Wu, 2008; Huang, 2017). As such, wage differences across firms are not ironed out by labor market competition. In fact, Knight and Li (2005) show evidence of the growing importance of profitability in wage determination, which has contributed to widening wage inequality.

Possibly offsetting these structural reforms is the fact that the state continues to exert powerful influences on the allocation of factors of production, which is reflected in productivity differences across regions and ownership types (World Bank, 2012).[1] Brandt et al. (2013) find that factor market distortions have increased significantly since 1997, reducing aggregate non-agricultural total factor productivity growth by half a percent a year.

In this paper, we study time variation in product and labor market imperfections in Chinese firms during one of the most important recent trade liberalization episodes, i.e. the years surrounding China's accession into the World Trade Organization (WTO) in 2001. More specifically, we investigate potential shifts in firms' regimes characterizing the type of competition prevailing in product and labor markets. The characterization of these competitiveness regimes is based on identifying gaps between variable inputs' marginal products and their costs, which is related to allocative inefficiencies in terms of their impact on aggregate productivity growth as shown by Petrin and Sivadasan (2013). To serve this purpose, we use annual Chinese firm-level data for the period 1999-2006 from annual surveys conducted by the National Bureau of Statistics (NBS).

This paper contributes to the above literature on two grounds. First, although the impact of China's WTO accession on the degree of liberalization, firm performance and welfare gains has

[1] Brandt and Zhu (2010) and Kamal and Lovely (2012) document persistent differences in returns to labor and capital between state-owned and non-state enterprises. Liutang and Danyang (2006) report increasing dispersion in the marginal product of labor across provinces. Bai and Cheng (2016) identify the main sources of labor misallocation within provinces.

been extensively analyzed, its joint impact on price distortions in product as well as labor markets has not been investigated before.[2] Second, this paper improves our understanding of the wage determination process in Chinese firms through investigating the rent-sharing mechanism that generates inter-firm wage dispersion. In particular, 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 increasing allocative inefficiencies through distorting factor prices and whether the balance of power has shifted after WTO entry.[3]

Our application uses an econometric framework that is developed in Dobbelaere and Kiyota (2017) and builds on Dobbelaere and Mairesse (2013). It allows for three-dimensional firm heterogeneity: product market power (price-cost markups), labor market imperfections (workers' bargaining power during worker-firm negotiations or firm's degree of wage-setting power) and revenue total factor productivity (TFP). Rather than imposing a particular imperfect labor market model on the data, we let the data determine a firm's regime of competitiveness in product and labor markets by estimating a reduced-form productivity model. The theoretical structural productivity model behind the econometric reduced-form productivity model nests two polar models of wage determination in imperfect labor markets in the seminal productivity model of Hall (1988) which allows to estimate price-cost markups: the strongly efficient bargaining model (one of the two canonical collective bargaining models; McDonald and Solow, 1981) allocates market power to employees through costs of firing, hiring and training while the static partial equilibrium monopsony model (Manning, 2003) allocates market power to employers through allowing workers to have heterogeneous preferences over workplace environments of different potential employers which generate upward-sloping labor supply curves to individual firms.

Methodologically, our application differs from Dobbelaere and Kiyota (2017) with respect to the testing procedure that we use to identify a firm's regime of competitiveness at any point in time. In particular, we implement the testing procedure of Kodde and Palm (1984, 1986) which is well suited to handling nonlinear restrictions on the parameters of the model and testing restrictions under the alternative as well as the null. As such, this paper also contribute to the statistical literature on designing tests for multivariate problems with equality constraints. The main empirical difficulty related to such large-sample hypothesis testing is the derivation of the weights of the weighted-χ^2 distribution. In our application, we compare the adequateness of several approximation methods, in particular the Monte Carlo simulation techniques and Binomial distribution, to determine the weights for the weighted-χ^2 distribution of the distance test of Kodde and Palm (1984) to test inequality restrictions. The main objective of such comparison is to identify the robustness and

[2] For WTO impact on the degree of liberalization, see Lardy (2004), on firm performance, see Brandt et al. (2012, 2017) and on welfare gains, see di Giovanni et al. (2014). Trade economists have a long tradition of investigating the procompetitive effect of globalization and have provided evidence using actual trade liberalization episodes (see Tybout, 2003; De Loecker and Goldberg, 2014; and Van Biesebroeck and De Loecker, 2016 for surveys).

[3] This contribution is closely related to a growing theoretical trade literature that emphasizes trade-induced variation in firm-specific wages as one of the main drivers of increased wage inequality. This literature takes the seminal contribution of Melitz (2003) as a point of departure and considers rent sharing to be the key mechanism through which trade-induced variation in rents are transmitted to variation in wages. There exist various heterogeneous-firms approaches to trade and wage inequality which all draw on imperfect labor markets but differ in terms of the rent-sharing mechanism between workers and firms that produces inter-firm wage disparities. For example, one approach focuses on search and matching frictions such that ex-post bargaining over the surplus of production can potentially induce wages to vary with revenue across firms (Davidson et al., 2008; Helpman et al., 2010; Felbermayr et al., 2011; Fajgelbaum, 2013; Coçsar et al., 2016), while another approach considers decentralized collective bargaining as generating inter-firm wage dispersion (Montagna and Nocco, 2013).

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 many empirical economic problems.

Our main findings are summarized as follows. First, the dominant regime of competitiveness for a particular Chinese manufacturing industry is stable over time. The dominant regimes in manufacturing industries are IC-MO (imperfect competition in the product market and monopsony in the labor market) and IC-EB (imperfect competition in the product market and efficient bargaining in the labor market). This finding signals the prevalence of allocative inefficiencies in product and labor markets through distorting (factor) prices in Chinese industries. As such, we find no suggestive evidence for a decline of such inefficiencies after trade liberalization through the WTO entry. This conclusion particularly holds for industries which consist of predominantly state-owned enterprises.

Second, the comparison of the exact weights, determined by using the method of Kodde and Palm (1984,1986), with the approximation methods indicates that the Monte Carlo simulation technique is a very good approximation. The Binomial distribution approximation performs worse compared to the Monte Carlo simulation technique due to the skewness of the weights distribution. However, the binomial distribution has the advantage that it is the easiest and fastest approximation method available. As such, we conclude that these approximation methods provide fairly accurate approximations of exact weights for the weighted-χ^2 distribution of the distance test, nullifying the burden of the computational complexity of determining the exact weights.

The plan 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 regime of competitiveness. Section 5 presents the Chinese firm panel data. Section 6 reports the outcome of the testing procedure, provides a discussion in light of WTO entry and compares several approximation methods and the exact method for determining the weights. Section 7 concludes.

2. Theoretical structural model with imperfect product and labor markets

A firm i at time t produces output using the following production technology:

$$Q_{it} = Q_{it}(N_{it}, M_{it}, K_{it}) \tag{1}$$

with (N_{it}, M_{it}) a vector of static inputs in production free of adjustment costs (labor and intermediate inputs) and K_{it} capital treated as a dynamic input in production (predetermined in the short run).

We assume that (i) $Q_{it}(\cdot)$ is continuous and twice differentiable with respect to its arguments, (ii) a firm takes the input price of materials as given, (iii) firms produce in a homogeneous good industry and compete in quantities (play Cournot)[4] and (iv) producers active in the market are maximizing short-run profits.

[4] This assumption is consistent with only observing a domestic industry-wide output price index and not firm-specific output prices.

Let us turn to the oligopolistic firm's short-run profit maximization problem. Firm i's short-run profits, π_{it}, are given by:

$$\pi_{it}=R_{it}-w_{it}N_{it}-j_{it}M_{it} \tag{2}$$

with $R_{it}=P_tQ_{it}$ an increasing and concave revenue function, P_t the price of the homogenous good at time t, and w_{it} and j_{it} the firm's input prices for N and M, respectively, at time t.

Firm i must choose the optimal quantity of output and the optimal demand for intermediate inputs and labor. The optimal output choice Q_{it} satisfies the following first-order condition:

$$\frac{P_t}{(C_Q)_{it}}=\left(1+\frac{s_{it}}{\eta_t}\right)^{-1}=\mu_{it} \tag{3}$$

with $(C_Q)_{it}$ the marginal cost of production, $s_{it}=\frac{Q_{it}}{Q_t}$ the market share of firm i, $\eta_t=\frac{\partial Q_t}{\partial P_t}\frac{P_t}{Q_t}$ the own-price elasticity of industry demand and μ_{it} firm i's price-cost mark-up. Under Cournot competition, differences in price-cost mark-ups across firms are generated by differences in productivity and market structure (s_{it},η_t).

The first-order condition for the optimal choice of intermediate inputs is given by setting the marginal revenue product of intermediate inputs equal to the price of intermediate inputs:

$$(Q_M)_{it}=\frac{j_{it}}{P_t}\left(1+\frac{s_{it}}{\eta_t}\right)^{-1} \tag{4}$$

Inserting Eq. (3) in Eq. (4) and multiplying both sides by $\frac{M_{it}}{Q_{it}}$ yields:

$$(\varepsilon_M^Q)_{it}=\mu_{it}\alpha_{it}^M \tag{5}$$

From Eq. (5), it follows that profit maximization implies that optimal demand for intermediate inputs is satisfied when a firm equalizes the output elasticity with respect to intermediate inputs, denoted by $(\varepsilon_M^Q)_{it}$, to the price-cost mark-up μ_{it} multiplied by the share of intermediate input expenditure in total sales, denoted by $\alpha_{it}^M=\frac{j_{it}M_{it}}{P_tQ_{it}}$.

Firm i's optimal demand for labor depends on the characteristics of its labor market. We distinguish three labor market settings (LMS): perfect competition or right-to-manage bargaining (PR), strongly efficient bargaining (EB) and static partial equilibrium monopsony (MO). For details, we refer to Dobbelaere and Mairese (2013).

Under PR, labor is unilaterally determined by firm i from short-run profit maximization, which implies the following first-order condition:

$$(\varepsilon_N^Q)_{it}=\mu_{it}\alpha_{it}^N \tag{6}$$

Under EB, the risk-neutral firm and its risk-neutral workers negotiate simultaneously over wages and employment in order to maximize the joint surplus of their economic activity. An efficient wage-employment pair is obtained by maximizing a generalized Nash product (the product of the weighted net gains to the firm and its workers), implying the following first-order condition for labor:

$$(\varepsilon_N^Q)_{it}=\mu_{it}\alpha_{it}^N-\mu_{it}\gamma_{it}(1-\alpha_{it}^N-\alpha_{it}^M) \tag{7}$$

with $\gamma_{it} = \frac{\phi_{it}}{1-\phi_{it}}$ the relative extent of rent sharing and ϕ_{it} the part of economic rents going to the workers or the degree of workers' bargaining power during worker-firm negotiations.

Under MO, firm i faces a labor supply $N(w)$, which is an increasing function of the wage w. Short-run profit maximization implies the following first-order condition for labor:

$$(\varepsilon_N^Q)_{it} = \mu_{it}\alpha_{it}^N \left(1 + \frac{1}{(\varepsilon_w^N)_{it}}\right) \tag{8}$$

with $(\varepsilon_w^N)_{it} \in \Re_+$ the wage elasticity of labor supply of firm i, measuring the degree of wage setting power that firm i possesses.

Using the first-order condition for intermediate inputs, we obtain an expression for firm i's price-cost mark-up (μ_{it}) and using the first-order conditions with respect to intermediate inputs and labor, we define firm i's joint market imperfections parameter (ψ_{it}) as follows:

$$\mu_{it} = \frac{(\varepsilon_M^Q)_{it}}{\alpha_{it}^M} \tag{9}$$

$$\begin{aligned}
\psi_{it} &= \frac{(\varepsilon_M^Q)_{it}}{\alpha_{it}^M} - \frac{(\varepsilon_N^Q)_{it}}{\alpha_{it}^N} && (10)\\
&= 0 \quad \text{if LMS=PR} && (11)\\
&= \mu_{it}\gamma_{it}\left[\frac{1-\alpha_{it}^N-\alpha_{it}^M}{\alpha_{it}^N}\right] > 0 \quad \text{if LMS=EB} && (12)\\
&= -\mu_{it}\frac{1}{(\varepsilon_w^N)_{it}} < 0 \quad \text{if LMS=MO} && (13)
\end{aligned}$$

3. Econometric model

In order to obtain consistent estimates of the output elasticities $(\varepsilon_N^Q)_{it}$ 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 the set of producers (denoted by the vector β). These two assumptions imply the following expression for the production function:

$$Q_{it} = F(N_{it}, M_{it}, K_{it}; \beta)\exp(\omega_{it}) \tag{14}$$

In order to obtain consistent estimates of the production function coefficients (β) for each of the 15 two-digit industries (which are defined in Section 4), we need to control for unobserved productivity shocks ω_{it}, which are potentially correlated with the firm's input choices. 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 as in e.g. unionized firms/industries.

We assume that productivity (ω_{it}) evolves according to an exogenous first-order Markov process. This allows us to 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}):

$$\omega_{it} = \mathrm{E}[\omega_{it}|I_{it-1}] + \xi_{it} = \mathrm{E}[\omega_{it}|\omega_{it-1}] + \xi_{it} = g(\omega_{it-1}) + \xi_{it} \tag{15}$$

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}:

$$m_{it} = m_t(n_{it}, k_{it}, \omega_{it}) \tag{16}$$

Eq. (16) shows that firm i's intermediate input demand decision is a function of the state variables n_{it}, k_{it} and ω_{it}. It is crucial that ω_{it} is the only unobservable entering the intermediate input demand function. This scalar unobservable assumption together with the assumption that $m_t(n_{it}, k_{it}, \omega_{it})$ is strictly increasing in ω_{it} conditional on n_{it} and k_{it} (strict monotonicity assumption)[5], allow to invert ω_{it} as a function of observables:

$$\omega_{it} = m_t^{-1}(m_{it}, n_{it}, k_{it}) \tag{17}$$

Considering the logarithmic version of Eq. (14) and allowing for an idiosyncratic error term including non-predictable output shocks and potential measurement error in output and inputs (ϵ_{it}) gives:

$$y_{it} = f(n_{it}, m_{it}, k_{it}; \beta) + \omega_{it} + \epsilon_{it} \tag{18}$$

where $y_{it} = q_{it} + \epsilon_{it}$ with ϵ_{it} assumed to be mean independent of current and past input choices.[6]

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):

$$\begin{aligned} y_{it} \quad = \quad & \beta_0 + \beta_n n_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{nn} n_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \\ & \beta_{nm} n_{it} m_{it} + \beta_{nk} n_{it} k_{it} + \beta_{mk} m_{it} k_{it} + \omega_{it} + \epsilon_{it} \end{aligned} \tag{19}$$

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

Substituting Eq. (17) in Eq. (19) results in a first-stage equation of the form:

$$y_{it} = f_{it} + m_t^{-1}(m_{it}, n_{it}, k_{it}) + \epsilon_{it} = \varphi_t(n_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{20}$$

[5] Melitz and Levinsohn (2006) show that this strict monotonicity assumption holds as long as more productive firms do not set inordinately higher markups than less productive firms. Under Cournot competition, lower marginal costs (higher ω_{it}) lead to an increase in a firm's usage of intermediate inputs at any level of residual demand.

[6] Note that $(\varepsilon_N^Q)_{it} = \frac{\partial \ln F(.)}{\partial \ln N_{it}}$ and $(\varepsilon_M^Q)_{it} = \frac{\partial \ln F(.)}{\partial \ln M_{it}}$. These output elasticities are by definition independent of a firm's productivity shock.

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. (20) and the moment condition $\mathrm{E}[\epsilon_{it}|I_{it}] = 0$ to obtain an estimate $\widehat{\varphi}_{it}$, of the composite term $\varphi_t(n_{it}, k_{it}, m_{it}) = f_{it} + m_t^{-1}(m_{it}, n_{it}, k_{it})$, which represents output net of ϵ_{it}. In our application, estimation of Eq. (20) 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 β, we can compute (up to a scalar constant) an estimate of ω_{it}:

$$\begin{aligned} \widehat{\omega}_{it}(\beta) &= \widehat{m}_t^{-1}(m_{it}, n_{it}, k_{it}) \qquad (21) \\ &= \widehat{\varphi}_{it} - \beta_0 - \beta_n n_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_{nn} n_{it}^2 - \beta_{mm} m_{it}^2 - \beta_{kk} k_{it}^2 \\ &\quad -\beta_{nm} n_{it} m_{it} - \beta_{nk} n_{it} k_{it} - \beta_{mk} m_{it} k_{it} \end{aligned}$$

In order to implement the second stage and to identify the production function coefficients, we need to recover the innovation to productivity (denoted ξ_{it}) to form moments on. Using Eq. (21), a consistent (non-parametric) approximation to $\mathrm{E}[\omega_{it}|\omega_{it-1}]$ is given by the predicted values from regressing nonparametrically $\widehat{\omega}_{it}(\beta)$ on $\widehat{\omega}_{it-1}(\beta)$. 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: $\mathrm{E}[\xi_{it}(\beta)\mathbf{d}] = 0$ where the set of instruments is:

$$\mathbf{d}_{it} = \left\{ n_{it-1}, m_{it-1}, k_{it}, n_{it-1}^2, m_{it-1}^2, k_{it}^2, n_{it-1}m_{it-1}, n_{it-1}k_{it}, m_{it-1}k_{it} \right\} \qquad (22)$$

Exploiting these moment conditions, we can now estimate the production function coefficients β using standard GMM and rely on block bootstrapping for the standard errors. The estimated production function coefficients $\widehat{\beta}$ 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:

$$(\widehat{\varepsilon}_N^Q)_{it} = \widehat{\beta}_n + 2\widehat{\beta}_{nn} n_{it} + \widehat{\beta}_{nm} m_{it} + \widehat{\beta}_{nk} k_{it} \qquad (23)$$

Similarly, we calculate the firm-year elasticity of output with respect to material as:[7]

$$(\widehat{\varepsilon}_M^Q)_{it} = \widehat{\beta}_m + 2\widehat{\beta}_{mm} m_{it} + \widehat{\beta}_{mn} n_{it} + \widehat{\beta}_{mk} k_{it} \qquad (24)$$

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:[8]

$$\widehat{\alpha}_{it}^N = \frac{w_{it}N_{it}}{P_t \frac{Y_{it}}{\exp(\epsilon_{it})}} \qquad (25)$$

[7] 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.

[8] This correction is important as it eliminates any variation in expenditure shares that comes from variation in output not correlated with $\varphi_t(n_{it}, k_{it}, m_{it})$.

$$\widehat{\alpha}_{it}^{M} = \frac{j_{it} M_{it}}{P_t \frac{Y_{it}}{\exp(\epsilon_{it})}} \tag{26}$$

Using Eqs. (23), (24), (25) and (26), we compute $\widehat{\mu}_{it}$ and $\widehat{\psi}_{it}$ follows:

$$\widehat{\mu}_{it} = \frac{(\widehat{\varepsilon}_M^Q)_{it}}{\widehat{\alpha}_{it}^M} \tag{27}$$

$$\widehat{\psi}_{it} = \frac{(\widehat{\varepsilon}_M^Q)_{it}}{\widehat{\alpha}_{it}^M} - \frac{(\widehat{\varepsilon}_N^Q)_{it}}{\widehat{\alpha}_{it}^N} \tag{28}$$

4. Classification and testing procedures

4.1. Classification procedure

Based on the estimates of $\hat{\mu}_{it}$ and $\hat{\psi}_{it}$, we are able to determine firm i's product market setting $PMS \in \{PC,\ IC\}$ and labor market setting $LMS \in \{PR,\ EB,\ MO\}$ at time t. Different combinations of product and labor market settings lead to a different regime of competitiveness $R \in \Re = \{PC\text{-}PR,\ IC\text{-}PR,\ PC\text{-}EB,\ IC\text{-}EB,\ PC\text{-}MO,\ IC\text{-}MO\}$ of firm i at time t. We apply the classification of Dobbelaere and Mairesse (2013), which is summarized in Table 1.

<Insert Table 1 about here>

4.2. Testing procedure

Distance test. Applying the classification procedure discussed above requires implementing a testing procedure that is capable of handling nonlinear restrictions on the parameters of the model and testing restrictions under the alternative as well as the null. 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.

The distance test builds upon the earlier work of Perlman (1969), Nüesch (1964,1966) and Gourieroux *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 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):

$$\boldsymbol{\gamma} = N^{\frac{1}{2}} h(\boldsymbol{\theta}) \qquad \text{and} \qquad \bar{\boldsymbol{\gamma}} = N^{\frac{1}{2}} h(\bar{\boldsymbol{\theta}}), \tag{29}$$

where N denotes the sample size.

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

$$\boldsymbol{\Sigma} = \frac{\partial h(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}'} \boldsymbol{\Omega} \frac{\partial h(\boldsymbol{\theta})'}{\partial \boldsymbol{\theta}} \qquad \text{and} \qquad \bar{\boldsymbol{\Sigma}} = \frac{\partial h(\bar{\boldsymbol{\theta}})}{\partial \bar{\boldsymbol{\theta}}'} \bar{\boldsymbol{\Omega}} \frac{\partial h(\bar{\boldsymbol{\theta}})'}{\partial \bar{\boldsymbol{\theta}}} \,. \tag{30}$$

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

$$||\boldsymbol{\mu}|| = \boldsymbol{\mu}' \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu} \,. \tag{31}$$

Kodde and Palm (1984,1986) distinguish between five different equality and inequality restrictions, which all slightly alter the definition of the test.

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

$$D = ||\bar{\boldsymbol{\gamma}}|| \,, \tag{32}$$

which is equivalent to the Wald test.

Second, if one wants to test $H_0\colon\ \boldsymbol{\gamma} = \mathbf{0}$ against the inequality restriction $H_1\colon\ \boldsymbol{\gamma} \geqslant \mathbf{0}$, with at least one strict inequality, the distance test becomes:

$$D = ||\hat{\boldsymbol{\gamma}}|| \,, \tag{33}$$

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

$$\min_{\boldsymbol{\gamma} \geqslant \mathbf{0}} \quad ||\bar{\boldsymbol{\gamma}} - \boldsymbol{\gamma}|| \,. \tag{34}$$

Third, 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:

$$D = ||\bar{\boldsymbol{\gamma}} - \tilde{\boldsymbol{\gamma}}|| \,, \tag{35}$$

where $\tilde{\boldsymbol{\gamma}}$ is the solution of (34), so the distance test equals the minimum of (34).

Fourth, consider $H_0\colon\ \boldsymbol{\gamma} = (\boldsymbol{\gamma}_1', \boldsymbol{\gamma}_2')' = \mathbf{0}$ against $H_1\colon\ \boldsymbol{\gamma}_1 \neq \mathbf{0},\ \boldsymbol{\gamma}_2 \geqslant \mathbf{0}$, where the partitioning of $\boldsymbol{\Sigma}$ corresponds to that of $\boldsymbol{\gamma}$, the distance test becomes:

$$\begin{aligned} D = ||\hat{\boldsymbol{\gamma}}|| = & \left(\bar{\boldsymbol{\gamma}}_1 - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\bar{\boldsymbol{\gamma}}_2\right)' \left(\boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}\right)^{-1} \left(\bar{\boldsymbol{\gamma}}_1 - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\bar{\boldsymbol{\gamma}}_2\right) \\ & + \hat{\boldsymbol{\gamma}}_2' \boldsymbol{\Sigma}_{22}^{-1} \hat{\boldsymbol{\gamma}}_2 \,, \end{aligned} \tag{36}$$

where $\hat{\boldsymbol{\gamma}}_1$ equals:

$$\hat{\boldsymbol{\gamma}}_1 = \bar{\boldsymbol{\gamma}}_1 + \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\left(\hat{\boldsymbol{\gamma}}_2 - \bar{\boldsymbol{\gamma}}_2\right) \,, \tag{37}$$

and $\hat{\boldsymbol{\gamma}}_2$ solves the following program:

$$\min_{\boldsymbol{\gamma}_2 \geqslant \mathbf{0}} \quad \left(\bar{\boldsymbol{\gamma}}_2 - \boldsymbol{\gamma}_2\right)' \boldsymbol{\Sigma}_{22}^{-1} \left(\bar{\boldsymbol{\gamma}}_2 - \boldsymbol{\gamma}_2\right) \,. \tag{38}$$

Fifth, when 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:

$$\begin{aligned} D = ||\bar{\boldsymbol{\gamma}} - \tilde{\boldsymbol{\gamma}}|| = &\left(\bar{\boldsymbol{\gamma}}_2 - \tilde{\boldsymbol{\gamma}}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right)' \left(\boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}\right)^{-1} \left(\bar{\boldsymbol{\gamma}}_2 - \tilde{\boldsymbol{\gamma}}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right) \\ &+ \bar{\boldsymbol{\gamma}}_1'\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\,, \end{aligned} \tag{39}$$

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

$$\min_{\boldsymbol{\gamma}_2 \geqslant \mathbf{0}} \quad \left(\bar{\boldsymbol{\gamma}}_2 - \boldsymbol{\gamma}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right)' \left(\boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}\right)^{-1} \left(\bar{\boldsymbol{\gamma}}_2 - \boldsymbol{\gamma}_2 - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\bar{\boldsymbol{\gamma}}_1\right)\,. \tag{40}$$

The equations (34), (38), and (40) can be solved by standard quadratic programming techniques (see Beale (1955) and Wolfe (1959)). These quadratic minimization problems can easily be rewritten in the following standard quadratic programming form[9]:

$$\min_{\boldsymbol{x} \geqslant \mathbf{0}} \quad \alpha + \boldsymbol{\beta}'\boldsymbol{x} + \frac{1}{2}\boldsymbol{x}'\boldsymbol{\Lambda}\boldsymbol{x}\,, \tag{41}$$

where α is a scalar, $\boldsymbol{\beta}$ and $\boldsymbol{x}$ vectors and $\boldsymbol{\Lambda}$ a symmetric matrix.

Let us now discuss the distribution of the several 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, $H_0\colon\ \boldsymbol{\gamma} = \mathbf{0}$ against the restricted alternative $H_1\colon\ \boldsymbol{\gamma} \geqslant \mathbf{0}$, with at least one strict inequality, is distributed under H_0 as

$$\mathbb{P}\left[D \geqslant c|\boldsymbol{\Sigma}\right] = \sum_{i=0}^{p} \mathbb{P}[\chi^2(i) \geqslant c]\; w(p, i, \boldsymbol{\Sigma})\,, \tag{42}$$

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

Third, 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

$$\mathbb{P}\left[D \geqslant c|\boldsymbol{\Sigma}\right] = \sum_{i=0}^{p} \mathbb{P}[\chi^2(p-i) \geqslant c]\; w(p, i, \boldsymbol{\Sigma})\,, \tag{43}$$

where $w(p, i, \boldsymbol{\Sigma})$ denotes the probability that i of the p elements of $\tilde{\boldsymbol{\gamma}}$ are strictly positive. Notice that the weights w for the second and third hypotheses are the same, as both $\hat{\boldsymbol{\gamma}}$ and $\tilde{\boldsymbol{\gamma}}$ solve Eq. (34). The only difference between the two conditional probabilities is the degree of freedom of the $\chi^2(i)$ distribution. In the latter, it decreases because of the inequality restrictions being imposed under the null.

Fourth, $H_0\colon\ \boldsymbol{\gamma} = (\boldsymbol{\gamma}_1', \boldsymbol{\gamma}_2')' = \mathbf{0}$ against $H_1\colon\ \boldsymbol{\gamma}_1 \neq \mathbf{0},\ \boldsymbol{\gamma}_2 \geqslant \mathbf{0}$ leads to the following distribution of the test statistic

$$\mathbb{P}\left[D \geqslant c|\boldsymbol{\Sigma}\right] = \sum_{i=0}^{p-q} \mathbb{P}[\chi^2(q+i) \geqslant c]\; w(p-q, i, \boldsymbol{\Sigma}_{22})\,, \tag{44}$$

[9] These derivations are available upon request.

where $w(p-q, i, \mathbf{\Sigma}_{22})$ denotes the probability that i of the $p-q$ elements of $\hat{\boldsymbol{\gamma}}_2$ are strictly positive, with q the number of equality restrictions and $\mathbf{\Sigma}_{22}$ corresponding to $\boldsymbol{\gamma}_2$.

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

$$\mathbb{P}\left[D \geqslant c|\mathbf{\Sigma}\right] = \sum_{i=0}^{p-q} \mathbb{P}[\chi^2(p-i) \geqslant c]\; w(p-q, i, \mathbf{\Sigma}_{22} - \mathbf{\Sigma}_{21}\mathbf{\Sigma}_{11}^{-1}\mathbf{\Sigma}_{12})\,, \tag{45}$$

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 $\bar{\boldsymbol{\gamma}}_1$.

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 program problems differ across hypotheses, so do the weights w. Let the weights w be 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 of one of the quadratic programming problems (34), (38) or (40), i.e. $\hat{\boldsymbol{\gamma}}$, $\tilde{\boldsymbol{\gamma}}$, $\hat{\boldsymbol{\gamma}}_2$ 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 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 Kûdo (1963), Shapiro (1985,1988) and Wolak (1987). 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 Bohrer and Chow (1978), Robertson and Wright (1983), Robertson *et al.* (1988) and Siskind (1976). Monte Carlo simulation techniques are proposed by Dardanoni and Forcina (1998), Gourieroux *et al.* (1982), Silvapulle (1996), Silvapulle and Sen (2011) and Wolak (1987). 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 upper and lower bound approximation, Kodde and Palm (1984,1986) derive a method to determine the weights using their statistical properties. Gourieroux *et al.* (1982) propose the binomial distribution approximation to be a simple and fast approximation technique.

We select a few methods to determine the weights. The general method of Kodde and Palm (1984,1986) 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 it does not have the caveat of scaling exponentially in m but this technique does not produce exact weights. The binomial approximation of Gourieroux *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.

The main objective of comparing these different methods is to identify the 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 many empirical economic problems. Such comparison can be done by using the ℓ^2-norm, also known as the Euclidean-norm, as a measure to determine the difference between two methods, where a small ℓ^2-norm distance indicates a good approximation. This approach entails the difficulty of evaluating whether or not a distance is small. Therefore, we opt to use a small modification of the approach of Robertson and Wright (1983)[10], which produces more intuitive results compared to the ℓ^2-norm approach.

The approach is as follows. A large set of random vectors $\boldsymbol{x}$ and variance-covariance matrices $\boldsymbol{U}$ is generated, which correspond to $\boldsymbol{\gamma}$ and $\boldsymbol{\Sigma}$ in the distance test of Kodde and Palm (1984,1986). First, the variance-covariance matrix $\boldsymbol{U}$ is sampled using a unit-Wishart distribution[11] with a small number of degrees of freedom, i.e. df $= 5$. The degrees of freedom control the variability of the sampled variance-covariance matrix. Since no prior information is known about the sampled variance-covariance matrix, we allow the variability in the sampling to be large. Next, the random vector $\boldsymbol{x}$ is a random draw from a multivariate normal with mean zero and variance-covariance matrix $\boldsymbol{U}$. The procedure continues by selecting a significance level α, e.g. 0.05. The exact critical value corresponding to this α is calculated, using the statistical properties of Kodde and Palm (1984,1986). The approximated weights, based on $\boldsymbol{x}$ and $\boldsymbol{U}$, are used to calculate an $\hat{\alpha}$, the probability of exceeding the true critical value. If this estimated probability $\hat{\alpha}$ is close to the true α a large number of times, the approximation method is believed to be adequate. In other words, the method indicates whether the change in the size of the test is substantial, stemming from the use of approximations for the weights.

5. Data

We use annual Chinese firm-level data for the period 1999-2006 from annual surveys conducted by the National Bureau of Statistics (NBS).[12] The survey includes all industrial firms that are either state-owned or are non-state firms with sales above 5 million RMB.[13] In addition, we use complementary information including industry concordances and deflators for all nominal variables, provided by Brandt *et al.* (2012).

Output (Q) is defined as real gross output measured by nominal production divided by a 4-digit industry output price index. Labor (L) 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 (IO) table. The capital stock (K) is measured by the real capital stock,

[10]The method differs slightly from that of Robertson and Wright (1983) as they check whether the exceedance probability of the exact method deviates from the exceedance probability of the approximation method, while we check the opposite.

[11]The sample variance of a one-dimensional normal distribution follows a χ^2 distribution. The Wishart distribution is the natural multidimensional extension of the χ^2 distribution. It can be shown that the Wishart distribution is the multidimensional extension of the distribution of the sample variance-covariance matrix of a multidimensional normal distribution.

[12]In this version, we employ a 20% random sample. We recently got access to the full sample, which we are currently exploiting.

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

computed from tangible assets and investment based on the perpetual inventory method and using the Brandt-Rawski deflator 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 undeflated production.

We focus only on manufacturing firms, assigning firms to 29 2-digit industries. 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 cost shares by industry 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 14,905 firms. Table A.1 in Appendix reports the panel structure of the estimation sample. Table A.2 reports the number of observations and firms by industry. Table 2 reports the means, standard deviations and quartile values of the main variables in our estimation sample.

<Insert Table 2 about here>

6. Results

Estimates of $\hat{\mu}_{it}$ and $\hat{\psi}_{it}$ are used to define simultaneously the product market setting $PMS \in \{PC,\ IC\}$ and labor market setting $LMS \in \{PR,\ EB,\ MO\}$ at time t for firm i . The resulting regime of competitiveness $R \in \Re = \{PC\text{-}PR,\ IC\text{-}PR,\ PC\text{-}EB,\ IC\text{-}EB,\ PC\text{-}MO,\ IC\text{-}MO\}$ of firm i at time t is determined by implementing the distance test of Kodde and Palm (1984,1986) through a system of Matlab functions at the significance level of 10%.

The panel nature of the data enable us to investigate time variation in a firm's regime of competitiveness over the period 1999-2006, which we tentatively relate to China's entry to the World Trade Organization in 2001. Given the large number of firms, we present results at the industry level. We consider two methods to move from the micro (firm) to the meso (industry) level. The first consists of aggregating the firm-year results at the industry level. The second uses a two-step aggregation. In a first step, we aggregate the firm-year results at the firm level and determine the prevailing regime for firm i. In the second step, we use the prevalent firm-specific regimes to obtain aggregation at the industry level. The first method entails the advantage of not imposing a priori restrictions.

The number of occurrences of each regime of competitiveness is determined at the firm-year level. These firm-year number of occurrences are aggregated at the industry level by summing up the firm-year level occurrences weighted by their share of value added for all firms within the industry, i.e.

$$\sum_{i \in \mathfrak{I}} w_i \left(\# \text{ of occurrences of regime } R\right)$$

where $\mathfrak{I}$ 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.

$$\sum_{i \in \mathfrak{I}} \frac{w_i \left(\# \text{ of occurrences of regime } R\right)}{\sum_{i \in \mathfrak{I}} w_i}$$

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 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 3 presents variation in regimes of competitiveness over the period 1999-2006 at the industry level.

<Insert Table 3 about here>

Table 3 shows that only a small fraction of industries (7 out of 29 or 24%) observe at least one change in competitiveness regime over time. This apparent stability of regimes suggests that the WTO effect was relatively small. 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.[14]

Let us now turn to the prevailing competitiveness regimes of each of the 29 industries, which we present in Table 4. The frequencies in Table 4 are denoted as fractions and are ranked according to their dominant regime and within their dominant regime on the basis of highest weighted frequency of occurrence. These frequencies may not necessarily sum up to 100% due to the fact that the distance test can be inconclusive. In our sample, the distance test is inconclusive for 91% of the cases. However, the test is in doubt between two competitiveness regimes in 66% of these inconclusive cases. This may be attributed to the fact that, in reality, firms seldom operate under a single theoretical extreme of both the product and labor market setting spectrum. Instead, it is more realistic to assume that firms operate under a hybrid combination of several extreme product and labor market settings. Indeed, a hybrid combination of several labor market settings that may be very common in reality is that of efficient bargaining and monopsony as most firms need to comply with some sort of collective bargaining agreement or minimum wage (favouring EB) and have, to some degree, wage-setting power due to job characteristics or lack of labor mobility (favouring MO). Another explanation may be that firms are currently in a transition

[14] For example, the regime of competitiveness of the tobacco industry changes from IC-PR in 1999 to IC-EB for the years 2000-2001. This change occurred due to the fact, that for a single firm, the distance test rejected the IC-PR regime for the years 2000-2001. Therefore, changes in regimes due to small fluctuations in the inconclusiveness of the distance test do not indicate underlying systematic changes to the environment in which the firms operate.

phase between different regimes due to trade liberalizations following from WTO entry. However, the fraction of inconclusive cases in the pre-WTO period (1999-2001) is not significantly different from the one in the post-WTO period (2002-2006), which does not seem to support the latter explanation.[15]

<Insert Table 4 about here>

Table 4 reveals that perfect competition in both product and labor markets is not very common across Chinese manufacturing industries, with an average fraction of occurrence just short of 10%. This confirms expectations as the *PC-PR* regime of competitiveness is often thought of to be a philosophical benchmark. Nevertheless, some of the highest fractions of occurrence of the *PC-PR* regime are in line with expectations, e.g. food and furniture. The two most dominant regimes of competitiveness at the industry level are *IC-MO* and *IC-EB*, with both an average fraction of occurrence over 63%. This indicates 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 *IC-EB* regim may be due to the level of unionization in China. Ge (2007) finds that unions in China have "real" effects on a firm's bargaining power. Unions increase the average wage level of unionized relative to non-unionized industries. Because unions are predominantly governed by the state, unionization is highest in state-owned enterprises (SOEs) and lowest in foreign-owned enterprises (FOEs). The industries which contain the highest share of SOEs such as petroleum, medical equipment, transport, minerals, nonferrous metal and ferrous metal correspond to industries with *IC-EB* as the dominant regime (see Table 4). Interestingly, more technologically advanced industries, e.g. computing, machinery and chemicals, experience more often wage-setting power compared to non-technological (classical) industries. Heterogeneous worker preferences for job characteristics might explain this finding.

Let us now discuss the volatility of competitiveness regimes at the industry level. The changes in the regime 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 1, 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 in regime of competitiveness and the radius corresponds to a measure of variation (standard deviation) of the average change. Table A.3 in Appendix presents the average change in regime of competitiveness at the industry level and within industry variation underlying Figure 1.

<Insert Figure 1 about here>

From Figure 1, it is clear that the size of the industry does not have an effect on either the average number of changes in regimes or the variation of the average change. The average change of the industries lies just below one, with not much variation across industries. However, there is more

[15]The difference in fraction of inconclusive cases is in the order of 0.3 percentage points between the two periods. For the fraction of inconclusive cases where the distance test is in doubt between two regimes of competitiveness this difference is in the order of 0.2 percentage points.

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 might be explained by differential effects of WTO entry on different subgroups within industries.

We now turn to discussing the documented changes in regimes in the light of China's accession to the WTO at the end of 2001. WTO entry may have had positive effects on the Chinese domestic economy. Due to trade liberalization, import tariffs for different industries converged to an almost low uniform level (Brandt *et al.*, 2017). Trade liberalization and output tariff declines induce pro-competitive effects, which causes prices to fall and might dampen price-cost mark-ups (Edmond *et al.*, 2015). On the other hand, marginal costs decline due to input tariff reductions, which might lead to an increase in price-cost mark-ups. Which effect dominates is a priori not clear. Brandt *et al.* (2017) find evidence for a dominating price effect and therefore, a strong pressure on the mark-ups of Chinese manufacturing firms. However, De Loecker *et al.* (2016) provide evidence of the fall in prices being small relative to the decrease in marginal costs, which invokes an increase in mark-ups. Price-cost mark-ups are essential in determining the competitiveness regime in our framework. Firm i's μ_{it} is present in the classification procedure in a self-contained manner and as a part of firm i's joint market imperfections parameter ψ_{it} . A downward pressure on the price-cost mark-ups should be in favor of the PC product market setting, while an increase should favor the IC product market setting.

WTO effects on a firm's labor market setting are not clear a priori, either. An increase in price-cost mark-ups influences the regime of competitiveness via the joint market imperfections parameter ψ_{it} . If μ_{it} increases, a firm might be more willing to share rents with their workers, which yields an increase in the frequency of labor market setting EB occurrences. On the other hand, if because of e.g. an increase in foreign direct investment (FDI) due to liberalization, intra-firm labor replacement increases (within-firm adjustment), a firm's wage-setting power might increase. This would induce an increase in the frequency of labor market setting MO occurrences. However, an increase in FDI due to liberalization might have pro-competitive effects by allowing for new fore

To study these effects, Table 5 reports the difference-in-difference in weighted frequency of occurrence of each regime compared to the dominant regime of competitiveness at the industry level before WTO entry (years 1999-2001) and after WTO entry (years 2002-2006), i.e.

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

where $\mathfrak{J}$ denotes the set of firms contained in industry j , $\hat{R}$ denotes the dominant regime and w_i denotes the weight, defined as the share of value added, of firm i . Δ denotes the difference operator and determines the difference between the pre-WTO period (1999-2001) and the post-WTO period (2002-2006).

<Insert Table 5 about here>

This Differences-in-Differences approach allows us to provide suggestive evidence on whether WTO entry has led to a shift in the dominant regimes of competitiveness. A large absolute value of the difference-in-difference change of certain regimes suggests the existence of an WTO entry impact on the regime of competitiveness in which firms/industries operate.[16] In order to highlight the importance of observed changes, we mark regimes in Table Table 5 as follows. First, * marks a regime displaying a difference-in-difference change exceeding 25 percentage points in absolute value. Second, † marks a regime that is more than 10 percentage points apart from the dominant regime prior to WTO entry and less than 10 percentage points apart after WTO entry. Third, ‡ marks a regime that is less than 10 percentage points apart from the dominant regime prior to WTO entry and is more than 10 percentage points apart after WTO entry.

Table 5 reveals large 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 entry.[17] Note that almost all large regime changes are not of great importance as these regimes are not decisive in determining an industry's dominant regimes, even after the large change. Focusing on the product market setting, we find that most relevant changes are in favor of the IC setting. Besides, IC is in both the pre- and post-WTO period the dominant product market setting. This might indicate that the fall in prices has been small relative to the marginal cost decrease, causing price-cost mark-ups to increase. These findings are in line with Brandt *et al.* (2017) who find that inefficiencies in SOEs remain after trade liberalization due to enjoying other forms of protection.

Focusing on the labor market setting, we find mixed results. More technologically advanced industries move towards the MO labor market setting, which might suggest that FDI is concentrated in these industries and does not entail pro-competitive effects. Industries consisting of predominantly SOEs are characterized by IC-EB in the pre-WTO period and predominantly operate under IC-EB in the post-WTO period as well. The composition of regimes is stable for several industries, e.g. nonferrous metal, ferrous metal, minerals and culture, education and sport. This can possibly be related to strong unionization in these industries (Chan, 2000; Ge, 2007), which in turn explains the dominant EB labor market setting.[18]

Summing up, we mainly observe a consolidation of pre-WTO dominant regimes after WTO entry. Most industries operate under imperfect competition in both product and labor markets, they mainly differ in their labor market setting. These differences can be traced back to differences in levels of unionization across industries. It seems that the position of the dominant regime IC-MO has been strengthened after WTO entry in industries that were characterized by this regime in the pre-WTO period. Meanwhile, the position of the dominant regime IC-EB seems to be under more pressure. All in all, we do not find suggestive evidence for declining levels of allocative inefficiencies

[16] This difference-in-difference change entails a composition effect as well as an WTO entry effect. The composition effect consists of changes in firms belonging to a specific regime during the period 1999-2006. The WTO entry effect refers to time variation in regimes due to e.g. trade liberalization. Isolating the causal impact of WTO entry on competitiveness regimes would require disentangling both effects.

[17] Changes that are marked with † or ‡.

[18] One industry that stands out is petroleum because of the substantial changes we observe. Besides, the petroleum industry is heavily unionized and consists of a few large SOEs. Table 5 shows a switch towards the IC product market setting, while the labor market setting is becoming more inconclusive. Several counteracting forces may be at work. On the one hand, liberalization might attract FDI which could induce a shift from EB towards MO. However, the observed slight shift towards PR indicates that pro-competitive effects of new foreign entrants may also be present. Meanwhile, the petroleum industry had a high level of unionization prior to WTO entry, which could have created a dampening effect on the move towards MO. The existence of inefficiencies in SOEs even after trade liberalization is again in line with the findings of Brandt *et al.* (2017).

in product and labor markets after trade liberalization, i.e. we do not observe a trend towards the PC or PR product respectively labor market setting.

Robustness of approximation methods for determining the weights in the weighted-χ^2 Distribution. As noted above, several approximation methods for determining the weights in the weighted-χ^2 distribution are compared to the exact weights. The latter are determined by exploiting the statistical properties derived by Kodde and Palm (1984,1986). The approximation methods consist of Monte Carlo simulation techniques and the Binomial distribution approximation. The procedure of Robertson and Wright (1983), with a slight modification, is used to compare the approximation methods with the exact weights. This procedure requires to calculate the exact weights and critical value for which some elements of the test statistic are necessary, e.g. the quadratic programming problem. Since the test statistic depends on the hypothesis that is tested, we select the second hypothesis from of Kodde and Palm (1984,1986) to check robustness. The hypothesis chosen does not affect the comparison of the different methods. It is selected for the sake of computational efficiency only. The same reasoning applies for the number of parameters which are considered in the comparison. Most approximation methods to determine the weights are only of interest to the researcher when the number of parameters is large. However, the number of parameters influence the computational complexity significantly. Therefore, we use the maximum number of parameters which is still feasible to determine using closed-form solutions (Kûdo (1963), Shapiro (1985,1988) and Wolak (1987)), i.e. the number of parameters is set to four. By doing so, the correctness of the exact weights derived by exploiting the statistical properties stated by Kodde and Palm (1984,1986) can be verified using these closed-form solutions. We select the $\alpha = 0.05$ significance level as is conventional in most economic testing problems. The number of repetitions for the procedure of Robertson and Wright (1983) is set to 10,000, in accordance with Robertson and Wright (1983).

Table 6 presents the results of the robustness check using the Monte Carlo simulation technique. From Table 6, it follows that most of the frequency mass lies around the true α of 0.05. This indicates that the Monte Carlo simulation technique is able to approximate the weights in the weighted-χ^2 distribution very well. The simulated weights all fall between 0.044 and 0.116, which points out that the Monte Carlo simulation approximated weights overestimate the exceedance probability more than underestimating it. Ideally, one would like to see no structural over- or under-estimation of the exceedance probability. This over-estimation of the exceedance probability may be due to the sensitivity settings of the Monte Carlo simulation. The simulation counts, in each replication, the number of strictly positive elements in the solution of the quadratic programming problem. Since it is a numerical procedure, exactly testing for observing a zero makes no sense because of the numerical error. Therefore, one should set some threshold such that a number below this threshold is considered to be zero. This choice of threshold might influence the distribution of approximated exceedance probabilities. We observe that the number of occurrences in the $[0.040, 0.060]$-interval is equal to 7,822, i.e. 78% of all Monte Carlo simulated weights are off by a maximum of 1 percentage point from the true exceedance probability. In these cases, the Monte Carlo simulation technique to approximate the weights give very accurate results. Approximations are judged to be very good when the approximated weights produce an exceedance probability that falls in the $[0.048, 0.052]$-interval, which is true for 3,829 out of the 10,000 simulations, or 38%

of the cases. The rate of convergence of the frequencies towards zero when moving away from the true α of 0.05, is rather fast.

<Insert Table 6 about here>

Table 7 presents the results of the robustness check using the Binomial distribution approximation. In contrast to the Monte Carlo simulation technique, the Binomial distribution seems to be less capable of producing accurate approximations. Most of the approximated weights generate exceedance probabilities that lie between 0.020 and 0.120. The maximum estimated exceedance probability that occurs in the 10,000 simulations is 0.264. Only for 933 of the 10,000 simulations, we observe a value for the approximated exceedance probability that is assessed to be very accurate. Adequate results are found when the approximated exceedance probability falls in the $[0.040, 0.060]$-interval, which occurs in 4,616 out of the 10,000 simulations, or 46% of the cases. Besides this small number of very good approximations, the rate at which the frequencies converge to zero is rather slow, especially in the area of over-estimating the exceedance probability.

<Insert Table 7 about here>

In sum, both the Binomial distribution and Monte Carlo simulation technique approximations produce adequate to very accurate approximations of the exact weight. The Monte Carlo simulation technique is –compared to the Binomial distribution– more able to capture the skewness in the distribution of the weights. The Binomial distribution assumes that both tails are evenly fat, therefore, generating cases in which all elements of $\boldsymbol{\xi}$ are zero and all are positive equal probabilities/weights. It is frequently observed that the distribution of the weights is skewed. This skewness depends on the variance-covariance matrix $\boldsymbol{\Delta}$, which can easily be seen from the closed-form solutions of Kûdo (1963), Shapiro (1985,1988) and Wolak (1987). In this comparison, due to the large number of simulations of random parameter vectors and variance-covariance matrices, the left- and right-skewed weights distributions occur as often.

Although Monte Carlo simulation techniques allow to capture the dynamics in the weights distribution, the main disadvantage of this approach is computational time. While this approach is faster than obtaining the exact weights using the method of Kodde and Palm (1984,1986) for a large number of elements of $\boldsymbol{\xi}$, its complexity increases faster in the number of elements compared to the Binomial distribution approximation due to the fact that a large number of replications is needed to approximate the weights accurately.[19]

7. Conclusion

The beginnings of the use of markets at the dawn of Chinese reform more than three decades ago has undoubtedly reduced distortions and enhanced efficiency. Yet, possibly offsetting these economic reforms is the fact that the state continues to exert considerable influence on the allocation of factors of production. Recent empirical evidence shows that factor market distortions have even

[19] An adequate solution for most research in economics, econometrics, biology, etc. might be to use a skewed distribution as an approximation for the weights. For a right-skewed weights distribution, the Exponential, Gumbell, log-normal or Weibull distributions can be used as an approximation. For a left-skewed weights distribution, the inverse Gumbell or Gompertz distributions are appropriate.

increased since the late 1990s, which suggests that China continues to suffer from total factor productivity losses.

In this paper, we study time variation in product and labor market imperfections in Chinese firms during one of the most important recent trade liberalization episodes, i.e. the years surrounding China's accession into the World Trade Organization (WTO) in 2001. More specifically, we investigate potential shifts in firms' regimes characterizing the type of competition prevailing in product and labor markets. The characterization of these competitiveness regimes is based on identifying gaps between variable inputs' marginal products and their costs, which is related to allocative inefficiencies in terms of their impact on aggregate productivity growth.

To serve this purpose, we apply a procedure to test inequality restrictions, the distance test of Kodde and Palm (1984, 1986), and use an unbalanced panel of Chinese manufacturing firms covering the period 1999-2006. The dominant regimes of competitiveness in manufacturing industries are IC-MO (imperfect competition in the product market and monopsony in the labor market) and IC-EB (imperfect competition in the product market and efficient bargaining in the labor market). The dominant regime for a particular Chinese manufacturing industry is stable over time. This finding signals the prevalence of allocative inefficiencies in product and labor markets through distorting (factor) prices in Chinese industries. As such, we find no suggestive evidence for a decline of such inefficiencies after trade liberalization through WTO entry. This conclusion particularly holds for industries which consist of predominantly state-owned enterprises. To promote the empirical applicability of the distance test, we show that existing approximation methods (Monte Carlo simulation techniques and Binomial distribution) provide fairly accurate approximations of exact weights in the weighted-χ^2 distribution of the distance test, nullifying the burden of the computational complexity of determining these exact weights.

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Table 1: Classification procedure of firm-year competitiveness regimes

$R = PC\text{-}PR$		
$H_0\colon\ \mu_{it} - 1 = \psi_{it} = 0$	against	$H_1\colon\ \mu_{it} - 1 \neq \psi_{it} \neq 0$
$R = IC\text{-}PR$		
$H_{01}\colon\ \mu_{it} - 1 > 0$	against	$H_{11}\colon\ \mu_{it} - 1 \not> 0$
$H_{02}\colon\ \psi_{it} = 0$	against	$H_{12}\colon\ \psi_{it} \neq 0$
$R = PC\text{-}EB$		
$H_{01}\colon\ \mu_{it} - 1 = 0$	against	$H_{11}\colon\ \mu_{it} - 1 \neq 0$
$H_{02}\colon\ \psi_{it} > 0$	against	$H_{12}\colon\ \psi_{it} \not> 0$
$R = PC\text{-}MO$		
$H_{01}\colon\ \mu_{it} - 1 = 0$	against	$H_{11}\colon\ \mu_{it} - 1 \neq 0$
$H_{02}\colon\ \psi_{it} < 0$	against	$H_{12}\colon\ \psi_{it} \not< 0$
$R = IC\text{-}MO$		
$H_{01}\colon\ \mu_{it} - 1 > 0$	against	$H_{11}\colon\ \mu_{it} - 1 \not> 0$
$H_{02}\colon\ \psi_{it} < 0$	against	$H_{12}\colon\ \psi_{it} \not< 0$
$R = IC\text{-}EB$		
$H_{01}\colon\ \mu_{it} - 1 > 0$	against	$H_{11}\colon\ \mu_{it} - 1 \not> 0$
$H_{02}\colon\ \psi_{it} > 0$	against	$H_{12}\colon\ \psi_{it} \not> 0$

Table 2: Descriptive statistics

	Mean	Sd.	Q_1	Q_2	Q_3	N
Real firm output growth rate Δq_{it}	0.117	0.280	-0.045	0.105	0.272	66,403
Labor growth rate Δn_{it}	0.027	0.209	-0.056	0.000	0.098	66,403
Materials growth rate Δm_{it}	0.099	0.306	-0.084	0.090	0.274	66,403
Capital growth rate Δk_{it}	0.050	0.475	-0.102	-0.016	0.143	66,165
$(\alpha_N)_j (\Delta n_{it} - \Delta k_{it}) + (\alpha_M)_j (\Delta m_{it} - \Delta k_{it})$	0.033	0.466	-0.142	0.054	0.232	66,146
$(\alpha_N)_i (\Delta k_{it} - \Delta n_{it})$	0.004	0.088	-0.018	-0.001	0.019	66,146
Solow Residual SR_{it}[a]	0.033	0.150	-0.041	0.030	0.107	66,146
Labor share in total revenue $(\alpha_N)_i$	0.152	0.110	0.072	0.126	0.202	81,279
Materials share in total revenue $(\alpha_M)_i$	0.763	0.099	0.708	0.769	0.825	81,308
Capital share in total revenue[b]	0.086	0.124	0.009	0.084	0.165	81,279
Employment (FTEs)	427	1,935	84	160	350	81,308

Note: [a] $SR_{it} = \Delta q_{it} - (\alpha_N)_j \Delta n_{it} - (\alpha_M)_j \Delta m_{it} - \left[1 - (\alpha_N)_j - (\alpha_M)_j\right] \Delta k_{it}$,
[b] $[1 - (\alpha_N)_i - (\alpha_M)_i]$.

Table 3: Time variation in dominant regimes of competitiveness by industry

IND	Industry	1999	2000	2001	2002	2003	2004	2005
1	Food proc.	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
2	Food	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
3	Beverages	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
4	Tobacco	*IC-PR*	*IC-EB*	*IC-EB*	*IC-PR*	*IC-PR*	*IC-PR*	*IC-PR*
5	Textile	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
6	Wear	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
7	Leather	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
8	Wood	*PC-MO*	*PC-MO*	*PC-MO*	*PC-MO*	*PC-MO*	*PC-MO*	*PC-MO*
9	Furniture	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
10	Paper	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*PC-MO*	*IC-EB*	*IC-EB*
11	Printing	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*PC-EB*
12	Cult. educ.	*PC-MO*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
13	Petroleum	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
14	Rawchem.	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
15	Med. equip.	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
16	Chem. fibres	*IC-PR*	*IC-PR*	*PC-EB*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
17	Rubber	*PC-EB*	*PC-EB*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
18	Plastic	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
19	Minerals	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
20	Ferr. metal	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
21	Nonferr. metal	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
22	Metal	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
23	Gen. mach.	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
24	Spec.mach.	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
25	Transport	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
26	Elec. mach.	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
27	Computing	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*	*IC-MO*
28	Meas. instr.	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*	*IC-EB*
29	NEC[a]	*IC-MO*	*IC-MO*	*IC-MO*	*IC-EB*	*IC-MO*	*IC-EB*	*IC-EB*

Note: [a]Not elsewhere classified

Table 4: Prevailing regimes of competitiveness at the industry level

IND	Industry	*PC-PR*	*IC-PR*	*PC-EB*	*PC-MO*	*IC-MO*	*IC-EB*	Dominant Regime
3	Beverages	0.31	0.43	0.43	0.83	0.40	1.00	*IC-EB*
9	Furniture	0.25	0.38	0.38	0.84	0.38	1.00	*IC-EB*
13	Petroleum	0.45	0.85	0.85	0.59	0.85	0.99	*IC-EB*
20	Ferr. metal	0.27	0.82	0.82	0.44	0.82	0.98	*IC-EB*
7	Leather	0.19	0.37	0.39	0.79	0.38	0.96	*IC-EB*
28	Meas. instr.	0.13	0.26	0.30	0.82	0.30	0.95	*IC-EB*
12	Cult. educ.	0.03	0.04	0.04	0.93	0.04	0.94	*IC-EB*
2	Food	0.21	0.74	0.78	0.42	0.78	0.93	*IC-EB*
21	Nonferr. metal	0.28	0.29	0.29	0.90	0.29	0.91	*IC-EB*
1	Food Proc.	0.12	0.40	0.45	0.65	0.45	0.90	*IC-EB*
15	Med. equip.	0.12	0.42	0.45	0.62	0.46	0.90	*IC-EB*
19	Minerals	0.03	0.07	0.11	0.79	0.11	0.82	*IC-EB*
29	NEC[a]	0.06	0.46	0.60	0.39	0.67	0.72	*IC-EB*
5	Textile	0.04	0.31	0.52	0.48	0.55	0.68	*IC-EB*
25	Transport	0.01	0.02	0.03	0.34	0.03	0.35	*IC-EB*
16	Chem. fibres	0.00	0.90	0.91	0.00	1.00	0.87	*IC-MO*
26	Elec. mach.	0.00	0.02	0.62	0.00	1.00	0.00	*IC-MO*
6	Wear	0.00	0.23	0.95	0.00	0.99	0.08	*IC-MO*
14	Raw chem.	0.01	0.64	0.96	0.02	0.99	0.52	*IC-MO*
18	Plastic	0.02	0.67	0.98	0.03	0.99	0.55	*IC-MO*
22	Metal	0.00	0.20	0.83	0.00	0.99	0.04	*IC-MO*
23	Gen. mach.	0.00	0.02	0.71	0.00	0.99	0.01	*IC-MO*
11	Printing	0.04	0.77	0.94	0.07	0.97	0.70	*IC-MO*
27	Computing	0.00	0.29	0.74	0.00	0.97	0.06	*IC-MO*
24	Spec. mach.	0.02	0.48	0.85	0.07	0.94	0.34	*IC-MO*
8	Wood	0.00	0.00	0.00	0.94	0.00	0.93	*PC-MO*
10	Paper	0.00	0.01	0.01	0.66	0.01	0.66	*PC-MO*
17	Rubber	0.00	0.98	1.00	0.00	1.00	0.95	*PC-EB*
4	Tobacco	0.21	1.00	1.00	0.10	1.00	1.00	*IC-PR*
Average fraction		0.10	0.42	0.58	0.40	0.63	0.68	

Note: [a]Not elsewhere classified

Table 5: WTO entry effect on competitiveness regimes at the industry level

IND	Industry	*PC-PR*	*IC-PR*	*PC-EB*	*PC-MO*	*IC-MO*	*IC-EB*
1	Food Proc.	−0.03	−0.13	−0.12	0.07	−0.12	-
2	Food	0.16	0.11	0.10‡	0.06	0.09‡	-
3	Beverages	−0.11	−0.25*	−0.25*	0.20‡	−0.35*	-
5	Textile	0.05	0.06	0.11‡	0.02	0.10‡	-
7	Leather	−0.08	−0.13	−0.14	0.04	−0.13	-
9	Furniture	0.11	0.08	0.08	0.01	0.08	-
12	Cult. Educ.	−0.10	−0.11	−0.11	0.01	−0.11	-
13	Petroleum	0.35*	−0.15†	−0.15†	0.51*‡	−0.16†	-
15	Med. Equip.	−0.07	−0.09	−0.09	0.02	−0.09	-
19	Minerals	−0.03	−0.03	−0.00	−0.00	−0.00	-
20	Ferr. Metal	0.20	0.08	0.08	0.14	0.08	-
21	Nonferr. Metal	−0.02	−0.01	−0.01	−0.01	−0.01	-
25	Transport	0.02	0.02	0.03	−0.01	0.03	-
28	Meas. Instr.	0.07	0.11	0.12	−0.04	0.12	-
29	NEC[a]	0.07	0.13	0.16‡	−0.05	0.15	-
6	Wear	−0.01	0.11	0.01	−0.01	-	0.04
11	Printing	0.06	0.01	0.02	0.06	-	0.05
14	Raw Chem.	−0.02	−0.24	−0.00	−0.02	-	−0.15
16	Chem. Fibres	−0.00	0.13‡	0.12‡	−0.00	-	0.18‡
18	Plastic	0.03	−0.13	0.01	0.03	-	−0.14
22	Metal	0.02	0.05	0.02	0.02	-	0.03
23	Gen. Mach.	−0.01	−0.02	−0.04	−0.01	-	−0.02
24	Spec. Mach.	0.01	0.05	−0.01	0.02	-	0.21
26	Elec. Mach.	0.00	−0.01	−0.08	0.00	-	0.00
27	Computing	0.02	0.17	0.18‡	0.02	-	0.10
8	Wood	−0.06	−0.06	−0.06	-	−0.06	−0.01
10	Paper	−0.14	−0.15	−0.15	-	−0.15	0.00
17	Rubber	−0.01	0.01	-	−0.01	−0.01	0.00
4	Tobacco	0.40*	-	0.00	0.18	0.00	−0.00

Note: [a]Not elsewhere classified

* denotes a regime that displays a difference-in-difference change exceeding 25 percentage points in absolute value. † denotes a regime that is more than 10 percentage points apart from the 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 dominant regime prior to WTO entry and more than 10 percentage points apart after WTO entry.

Table 6: Robustness of Monte Carlo simulation technique as an approximation for the weights

Interval	Frequency	Interval	Frequency
[0.044, 0.048]	120	[0.080, 0.084]	80
[0.048, 0.052]	3,829	[0.084, 0.088]	27
[0.052, 0.056]	2,626	[0.088, 0.092]	22
[0.056, 0.060]	1,247	[0.092, 0.096]	20
[0.060, 0.064]	720	[0.096, 0.100]	4
[0.064, 0.068]	488	[0.100, 0.104]	2
[0.068, 0.072]	376	[0.104, 0.108]	0
[0.072, 0.076]	265	[0.108, 0.112]	1
[0.076, 0.080]	172	[0.112, 0.116]	1

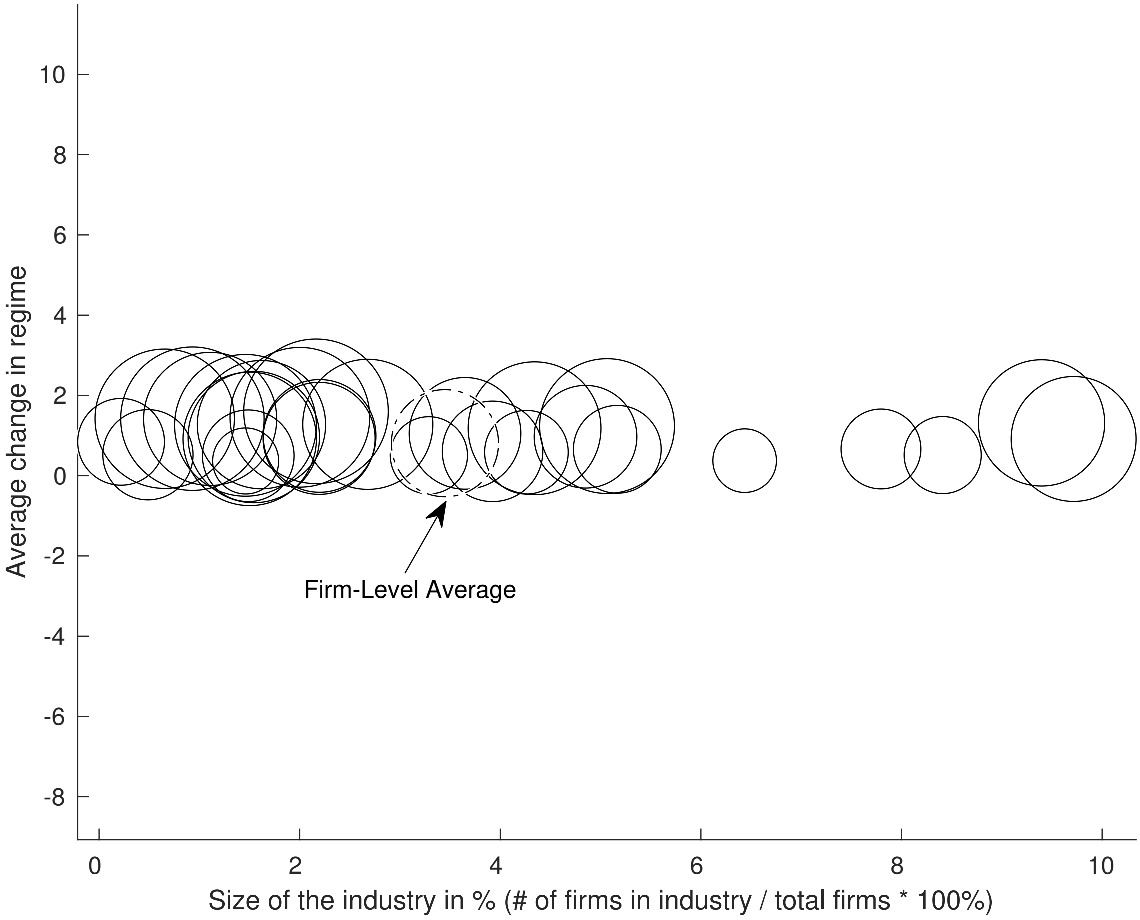
Frequency distribution of $\mathbb{P}[D \geqslant c|\mathbf{\Sigma}]$, with Monte Carlo simulation approximated weights, based on 10,000 randomly generated parameter vectors and corresponding variance-covariance matrices. c denotes the critical value determined by the exact method of Kodde and Palm (1984,1986).

Table 7: Robustness of Binomial distribution as an approximation for the weights

Interval	Frequency	Interval	Frequency
[0.020, 0.024]	4	[0.072, 0.076]	293
[0.024, 0.028]	82	[0.076, 0.080]	216
[0.028, 0.032]	392	[0.080, 0.084]	170
[0.032, 0.036]	826	[0.084, 0.088]	146
[0.036, 0.040]	1,053	[0.088, 0.092]	121
[0.040, 0.044]	1,186	[0.092, 0.096]	117
[0.044, 0.048]	1,091	[0.096, 0.100]	97
[0.048, 0.052]	933	[0.100, 0.104]	92
[0.052, 0.056]	771	[0.104, 0.108]	71
[0.056, 0.060]	635	[0.108, 0.112]	55
[0.060, 0.064]	502	[0.112, 0.116]	41
[0.064, 0.068]	425	[0.116, 0.120]	36
[0.068, 0.072]	333	[0.120, ∞]	312

Frequency distribution of $\mathbb{P}[D \geqslant c|\mathbf{\Sigma}]$, with Binomial distribution approximated weights, based on 10,000 randomly generated parameter vectors and corresponding variance-covariance matrices. c denotes the critical value determined by the exact method of Kodde and Palm (1984,1986).

Figure 1: 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 total number of firms which belong to the industry.

Appendix

Table A.1: Panel structure

# of Participations[a]	# Obs.	%	# Firms	%
4	21,984	27.04	5,496	36.87
5	17,490	21.51	3,498	23.47
6	12,972	15.95	2,162	14.51
7	7,910	9.73	1,130	7.58
8	20,952	25.77	2,619	17.57
Total	81,308	100.00	14,905	100.00

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

Table A.2: Industry composition

IND	Industry	# Firms	# Obs
1	Food proc.	647	3,474
2	Food	343	1,789
3	Beverages	217	1,217
4	Tobacco	32	167
5	Textile	1,355	7,464
6	Wear	710	3,500
7	Leather	300	1,646
8	Wood	236	1,217
9	Furniture	148	767
10	Paper	550	3,097
11	Printing	313	1,750
12	Cult. educ.	210	1,213
13	Petroleum	100	529
14	Raw chem.	1,102	6,179
15	Med. equip.	367	2,106
16	Chem. fibres	89	425
17	Rubber	208	1,197
18	Plastic	753	3,993
19	Minerals	1,410	7,612
20	Ferr. metal	311	1,773
21	Nonferr. metal	215	1,235
22	Metal	813	4,373
23	Gen. mach.	1,216	6,895
24	Spec. mach.	615	3,136
25	Transport	762	4,170
26	Elec. mach.	934	5,276
27	Computing	490	2,720
28	Meas. instr.	186	978
29	NEC[a]	273	1,410
Total		14,905	81,308

Note: [a]Not elsewhere classified

Table A.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.	4.34	1.18	1.65
2	Food	2.19	0.93	1.40
3	Beverages	1.54	0.96	1.64
4	Tobacco	0.22	0.84	1.08
5	Textile	9.40	1.32	1.57
6	Wear	4.26	0.59	1.04
7	Leather	2.00	1.46	1.74
8	Wood	1.49	0.50	1.14
9	Furniture	0.93	1.42	1.79
10	Paper	3.92	0.61	1.25
11	Printing	2.20	0.99	1.40
12	Cult. educ.	1.50	0.92	1.66
13	Petroleum	0.65	1.42	1.74
14	Raw chem.	7.80	0.67	0.99
15	Med. equip.	2.68	1.28	1.62
16	Chem. fibres	0.49	0.52	1.12
17	Rubber	1.46	0.37	0.82
18	Plastic	4.85	0.97	1.28
19	Minerals	9.72	0.91	1.56
20	Ferr. metal	2.16	1.60	1.80
21	Nonferr. metal	1.46	1.25	1.77
22	Metal	5.17	0.66	1.09
23	Gen. mach.	8.41	0.51	0.96
24	Spec. mach.	3.65	1.05	1.39
25	Transport	5.06	1.24	1.68
26	Elec. mach.	6.44	0.37	0.79
27	Computing	3.29	0.51	0.96
28	Meas. instr.	1.11	1.41	1.66
29	NEC[a]	1.62	1.27	1.60
Firm-level avg.		3.45	0.81	1.33

Note: [a]Not elsewhere classified

This table reports the underlying numbers of Figure 1. For each of the 29 industries, i.e. the number of average changes in regime of competitiveness and variation (standard deviation) within industries. The size of each industry is determined as the fraction of the total number of firms operating in each particular industry.