WORKING PAPER

Unveiling productivity and markup bias: the role of price heterogeneity

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Date:
March 2025

Keywords:
Productivity, Markups, Prices
JEL: D22, D24, D42, D43, E24, O47

Acknowledgements:
We would like to thank Karen Jackson, Schmerer Hans-Jörg, Benjamin Schwanebeck, as well as to workshop participants at the Global Economic Policy Group meeting 2024 at FernUniversität in Hagen, Berlin. Contact author: j.mei@westminster.ac.uk (Jen)

Abstract

Estimates of Total Factor Productivity (TFP) and markups are often biased due to unobserved price heterogeneity across firms. This paper adopts a structural approach to adjust for this bias. Using firm-level data from Chinese manufacturing firms for the period 1998–2007, we use a structural approach to the revenue function, incorporating firm-level input and output prices to disentangle TFP and markups from price variations. Using these estimates as a comparison, we find that omitting firm-level prices in the conventional approach significantly underestimates both the level and growth of aggregate TFP. Similarly, markup levels are substantially underestimated when firm-level price heterogeneity is omitted although markup growth is lower. These findings highlight the necessity of carefully taking into account the often-unobserved firm level price heterogeneity in order to interpret productivity and markup results meaningfully.

1. Introduction

Despite extensive research on measuring firm-level total factor productivity (TFP), the empirical literature faces a significant challenge in identifying productivity gains within firms. This is because output prices and values of physical quantities are frequently unobserved when estimating production functions (Klette and Griliches, 1996), leaving researchers using firm-level revenue data but industry-level prices to measure output, which leaves critical gaps in understanding firm-specific productivity dynamics. For the existence of firm-level price heterogeneity, even within narrowly defined sectors, means revenue-based TFP measures can differ substantially from quantity-based measures (Blackwood, Foster, Grim, Haltiwanger, and Wolf, 2021). For example, Garcia-Marin and Voigtländer (2019) and Bond, Hashemi, Kaplan, and Zoch (2021) show that conventional revenue-based TFP estimates fail to capture crucial information related to firms' quality adjustments in production and pricing. When a firm makes a quality improvement, revenue-based TFP tends to be downward biased, as firms facing a downward-sloping demand curve and must reduce prices to increase sales.

Firm-level input prices are just as essential as output prices for accurately assessing true technical efficiency (Kugler and Verhoogen, 2012; De Loecker and Goldberg, 2014; De Loecker, Goldberg, Khandelwal, and Pavcnik, 2016). An input price bias occurs when expenditure is used as the proxy for input costs, particularly, when firm-level input quantities and, more importantly, input prices are unavailable. In such cases, price rigidities – such as wage contracts or government-regulated prices – can prevent the full pass-through of input prices into output prices, leading to biases in the estimated elasticities and productivity.

Therefore, accounting for both output and input price variations is essential for obtaining accurate TFP estimates. Although widely used, the primal approach to this problem (Hall, 1988; De Loecker and Warzynski, 2012) faces various empirical criticisms. The approach does not require structural assumptions about demand and market competition, relying solely on cost minimization of flexible inputs. Yet despite its computational appeal, it is sensitive to the selection of variable inputs (Raval, 2023; CMA 2024) and to bias emerging from neglecting input adjustment costs (Bond et al., 2021). The weakness of the primal approach is related to identification bias from lacking firm-level output and input prices when it comes to estimating production functions. This issue is evident in the findings of Foster, Haltiwanger, and Tuttle (2022) and De Ridder, Grassi, and Morzenti (2024), which show significant bias and variation in output elasticities at different aggregation levels when revenue data are used without observing firm-specific output prices.

Using Chinese firm-level manufacturing data, in this paper we employ a structural approach with to demonstrate the biases in estimating production function parameters and TFP that arise from ignoring input and output price heterogeneity. Much of the literature relies on revenue or sales data from financial balance sheets to derive elasticities, while data on firm-level quantities remain unavailable. We calculating output prices at firm level as unit values, derived from the ratio of total sales to quantities sold, as we have the latter data. Coyle et al. (2024) correct for output price bias by augmenting the firm-level production function with deflated industry revenue, which is used as an additional input in the estimation. However, including solely deflated industry revenue in the firm-level production function does not capture all possible sources of bias from input and output price heterogeneity. In this paper we incorporate output prices within a revenue function methodology, building on Coyle et al. (2024), while also addressing input price bias arising from unobserved quality differences. To mitigate the latter source of bias, we use observable factors such as a firm's market share, export status, location (city and province), and foreign investment status (measured by foreign funds received) as proxies for these differences. We obtain implied output elasticities from estimates of production functions across twenty-eight manufacturing sectors. We can thus incorporate both output and input price heterogeneity within our structural approach. We discuss the detail in Section 2.

Alongside the estimation of firm-level production functions and the derivation of TFP taking price heterogeneity into account, we also focus on the measurement of markups. Given the importance of markups in assessing market power, our proposed methodology can be used to obtain more accurate markup estimates using revenue data taking into account the bias from omitted input and output price heterogeneity across firms. To derive markups, we employ an extended structural approach that accounts for both output and input prices, assuming a Cournot market structure and incorporating the elasticity of industry revenue substitution and a firm's market share. Following Atkeson and Burstein (2008), we assume that firms with larger market shares perceive a lower elasticity of demand (i.e., lower the elasticity of industry revenue substitution) and, as a result, set higher markups. This contrasts with the commonly used primal approach, which relies on output elasticities of a designated variable input (e.g., labor) and input expenditures, leading to downward biased markup estimates (Kirov, Mengano, and Traina, 2023; Klette and Griliches, 1996).

Our findings are summarized as follows: First, the estimation of the extended revenue production function reveals significant differences in TFP levels after accounting for input and output price heterogeneity. When price heterogeneity is not accounted for, TFP and markups tend to be systematically downward biased across all firms because the elasticities of both variable and fixed inputs are overstated.

Second, variations in prices also affect the estimated growth of TFP and markups. After taking into account firm-level input and output price heterogeneity we find TFP growth for our sample for the period 1998 to 2007 was 30%, significantly higher than the less than 20% growth when firm-level price differences are ignored. Regarding markups, we observe a decline of over 0.2% from 1998 to 2007, contrasting with the nearly constant levels when firm-level price differences are ignored.

Third, price heterogeneity affects the decomposition of TFP growth into within-firm, reallocation and net entry dynamics. Without price heterogeneity adjustment, the net entry term decreases by approximately 6-7% by the end of 2007. However, the net entry contribution to TFP is significantly more negative, nearly doubling to more than 12% by the end of 2007. For markups, the net entry contribution is estimated as positive for the period 1998–2007 when price heterogeneity is not controlled for, whereas it is negative when price differences are accounted for. This finding is robust to an alternative dynamic decomposition (provided in an Appendix).

The remainder of this paper proceeds as follows: Section 2.1 outlines the estimation framework using the structural demand approach to identify both revenue-based and quality-adjusted TFP. In Section 2.2, we derive markup estimates under the assumption of a specific market structure. In Section 3.1we then utilise firm-level total output and revenue data to derive firm-level output prices, adjusting for quality and revenue-based TFP within the structural approach. In Section 3.2, we address input prices by estimating a specific input quality equation, based on firms' output prices (quality), market share, export status, location, and foreign status, following De Loecker et al. (2016). Section 3.3 outlines our estimation strategy. Section 4 provides information on the data used in this paper, and Section 5 sets out the results. We conclude in Section 6.

2. A structural demand framework for TFP and markups

2.1 From firm revenue function to productivity

The main objective of this paper is to incorporate heterogeneous prices within a more structural production function framework that allows the derivation of TFP and markup measures. We begin with the basic set-up.

Firm-level demand. We start with a representative consumer with a CES utility function of the quality-adjusted goods produced by the N firms in the industry, as in Melitz (2000):

$$U_t\left(\left(\left[\sum_{i=1}^{N}\left(\Lambda_{ijt}\mathrm{Q}_{ijt}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}\right), Z_t\right), \tag{1}$$

where Z_t represents aggregate industry demand shifter, Λ_{ijt} is a measure of the quality of the good produced by firm i sector j at time t (where quality improvements result from changes to product characteristics that are valued by consumers), Q_{ijt} is the volume output produced by firm i sector j at time t, and η captures the elasticity of substitution between the N goods in the output index.

We incorporate both a representative consumer with a preference for variety, and vertical differentiation based on quality between products that enter into the industry output index. We denote quality-adjusted output as $Q_{ijt}^{*} = \eta_{jt}\mathrm{Q}_{ijt}$. We assume that $\eta > 1$ and that each firm produces a single product variety. Given the allocation of income to manufacturing goods, the demand function facing a given firm producing a good with quality Λ_{ijt} is derived as:

$$Q_{ijt} = \Lambda_{ijt}^{\eta-1}\left(\frac{P_{ijt}}{P_{jt}}\right)^{-\eta}\frac{\alpha P_t Y_t}{P_{jt}} \tag{2}$$

where α represents the proportion of income the representative consumer allocates to manufacturing goods (i.e., $P_{Zt}Z_t = \alpha P_t Y_t$ for manufacturing goods and $P_{Xt}X_t = (1-\alpha)\, P_t Y_t$ for others), and the price index for the industry, P_{jt}, is given by:

$$P_{jt} = \left[\sum_{i=1}^{N}\left(\frac{P_{ijt}}{P_{jt}}\right)^{\eta-1}\right]^{\frac{1}{\eta-1}} \quad (3)$$

Eq. (3) implies that quality improvements (Λ_{ijt}) are reflected in a lower industry price index. Moreover, a change in a particular good's Λ_{ijt}captures relative as well as absolute changes in quality (Fisher, 1965; Hulten, 1992; Coyle et al., 2024).

Firm production function. Turning to production side of the economy, we assume each firm has the Cobb-Douglas production function:

$$Q_{ijt} = \Omega_{ijt} L_{ijt}^{\beta_l} K_{ijt}^{\beta_k} M_{ijt}^{\beta_m} \quad (4)$$

where Ω_{ijt} is a (firm-specific) measure of Hicks-neutral technical change, L_{ijt} is labour, K_{ijt} is fixed capital, and L_{ijt} is materials.

Firm revenue function. In order to derive the revenue function, it is useful to write the demand function (5) in inverse form as:

$$\frac{P_{ijt}}{P_{jt}} = \Lambda_{ijt}^{\frac{\eta-1}{\eta}} Q_{ijt}^{-\frac{1}{\eta}} \frac{\alpha P_t Y_t}{P_{jt}}. \quad (5)$$

where the quality adjustment factor, Λ_{ijt}, is a shift factor for the inverse demand function that can reflect changes in quality corresponding to changes in the representative consumer's marginal willingness to pay. Using (4) and (5), total deflated firm revenue is:

$$\frac{R_{ijt}}{P_{jt}} = \left(\Lambda_{ijt} \mathrm{Q}_{ijt}\right)^{\frac{\eta-1}{\eta}} L_{ijt}^{\beta_l\left(\frac{\eta-1}{\eta}\right)} K_{ijt}^{\beta_k\left(\frac{\eta-1}{\eta}\right)} M_{ijt}^{\beta_m\left(\frac{\eta-1}{\eta}\right)} \left(\frac{R_{jt}}{P_{jt}}\right)^{\frac{1}{\eta}}, \quad (6)$$

where industry revenue is $R_{jt} = P_{jt} Z_t = \alpha P_t Y_t$ and firm-level revenue is $R_{ijt} = P_{ijt} Q_{ijt}$.

Next, we define the measure of revenue-based total factor productivity (TFPR) for firm i in period t as Ψ_{ijt}. Using the analogy with the representation of technical progress in a production function, we identify Ψ_{ijt} based on a general multiplicative form of the revenue function:

$$Q_{ijt} = \Psi_{ijt} G\left(L_{ijt}, K_{ijt}, M_{ijt}\right), \tag{7}$$

Given the specific form of the revenue function (7), TFPR is thus defined as:

$$\Psi_{ijt} = \left(\Lambda_{ijt} Q_{ijt}\right)^{\frac{\eta-1}{\eta}} \left(\frac{R_{jt}}{P_{jt}}\right)^{\frac{1}{\eta}}. \tag{8}$$

From (8), we see that total revenue varies with the increased use of factors of production for two reasons. First, an increase in the use of a factor of production (say labour) leads to an increase in physical output; and second, the firm must lower its price to sell the increased level of output given that it faces a downward sloping demand curve. The coefficient on each input is the revenue elasticity of the input, $(\eta - 1/\eta)\beta_f$for $f \in (l, k, m)$,where the revenue elasticity will be lower than the output elasticity given our assumption that $\eta > 1$.

TFP measures. Taking natural logs of (6) and rearranging we obtain:

$$r_{ijt} - p_{jt} = \frac{1}{\eta}\left(r_{jt} - p_{jt}\right) + \frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_k}{\eta} k_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt} + \frac{\eta-1}{\eta}\left(\lambda_{ijt} + \omega_{ijt}\right), \tag{9}$$

where lower case letters represent the natural log of a variable. A critical feature of (9) is that identification of η is possible from the coefficient on the deflated-industry-revenue variable in the estimated revenue equation (Klette and Griliches, 1996). Hence, Eq. (9) is used to estimate revenue function parameters. We can then derive our natural log of TFPR as:

$$\begin{aligned} \Psi_{ijt} &= \frac{\eta-1}{\eta}\left(\lambda_{ijt} + \omega_{ijt}\right) + \frac{1}{\eta}\left(r_{jt} - p_{jt}\right) \\ &= r_{ijt} - p_{jt} - \left(\frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_k}{\eta} k_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt}\right), \end{aligned} \tag{10}$$

Furthermore, we can define the natural log of quality adjusted TFP, TFPQ* (which includes product quality, technical efficiency, and price components), as:

$$(\lambda_{ijt} + \omega_{ijt})^{*} = \frac{\eta}{\eta-1}\Psi_{ijt} - \frac{1}{\eta-1}(r_{jt} - p_{jt}). \quad (11)$$

With revenue data alone it will be impossible to separately identify the effects of λ_{ijt} (quality adjustment factor) and ϖ_{ijt} (physical productivity).

2.2 Measuring markups under imperfect competition

To back out the markup measure under different market structures,[1] we need to obtain an estimate of the elasticity of substitution η highlighted in Eq. (9). We assume that firms face Cournot competition.[2] After solving for Cournot equilibrium, we obtain firm-level time-varying markups (Atkeson and Burstein, 2008).

Under the assumption of Cournot competition, firm i chooses output taking the output choice of firm i' in the industry as given. Industry output must be taken into account to identify the firm's perceived price elasticity of demand and consequent optimal markup. While each firm is thereby sufficiently large in relation to their industry, we assume that each firm is sufficiently small in relation to the total economy ignoring any effect on aggregate total output (Y_t) and aggregate total economy price index (P_t). Considering that $P_{jt}Z_t = \alpha P_t Y_t$, we substitute the industry price index out of inverse demand curve (Eq. 8):

$$\frac{P_{ijt}}{P_t} = \Lambda_{ijt}^{\frac{\eta-1}{\eta}} Q_{ijt}^{-\frac{1}{\eta}} \frac{\alpha Y_t}{Z_t}, \quad (12)$$

We can then write the elasticity of the industry output index with respect to firm i's output choice as (using Eq.4):

[1] Also see Forlani, Martin, Mion, and MuŬls (2023) for a useful exposition of the solution technique.

[2] Our framework also allows markups to be derived under the assumption of monopolistic competition. However, under this market structure firms set prices and quantities taking industry prices and quantities as given. Therefore, the markup in a monopolistically competitive market will be common across firms and constant over time: $\mu = \frac{\eta}{\eta-1}$.

$$\frac{dZ_t}{dQ_{ijt}}\frac{Q_{ijt}}{Z_t} = \left[\sum_{i=1}^{N}\left(\Lambda_{ijt}Q_{ijt}\right)^{\frac{\eta-1}{\eta}}\right]^{-1}\left(\Lambda_{ijt}Q_{ijt}\right)^{\frac{\eta-1}{\eta}}, \tag{13}$$

Multiplying both sides of Eq. (5) by Q_{ijt}/Z_t, we obtain the revenue share of firm i as s_{ijt} in industry revenue:

$$s_{ijt} = \frac{P_{ijt}Q_{ijt}}{P_{jt}Z_t} = \left[\sum_{i=1}^{N}\left(\Lambda_{ijt}Q_{ijt}\right)^{\frac{\eta-1}{\eta}}\right]^{-1}\left(\Lambda_{ijt}Q_{ijt}\right)^{\frac{\eta-1}{\eta}}. \tag{14}$$

and thus, from equation (13) and equation (14) we have $s_{ijt} = \frac{dZ_t}{dQ_{ijt}}\frac{Q_{ijt}}{Z_t}$. Taking natural logs of (14) and rearranging we have:

$$p_{ijt} = p_t + \left(\frac{\eta-1}{\eta}\right)\lambda_{ijt} - \frac{1}{\eta}q_{ijt} + \frac{1}{\eta}z_t + ln\alpha + y_t - z_t, \tag{15}$$

where $\lambda_{ijt} = ln\Lambda_{ijt}$. The partial derivative of p_{ijt} with respect to q_{ijt} is:

$$\frac{dp_{ijt}}{dq_{ijt}} = -\frac{1}{\eta}\left(1 - s_{ijt}\right) - s_{ijt}, \tag{16}$$

Multiplying the inverse of Eq. (16) by -1 gives an expression of the absolute price elasticity of demand:

$$\frac{dp_{ijt}}{dq_{ijt}} = \frac{1}{\frac{1}{\eta}(1-s_{ijt})+s_{ijt}}, \tag{17}$$

We can now use the standard markup (μ) formula, to obtain variable markup under Cournot competition:

$$\mu_{ijt} = \left(\frac{1}{1-s_{ijt}}\right)\left(\frac{\eta}{\eta-1}\right). \tag{18}$$

where η is derived using the estimated elasticity of substitution from Eq. (10), and s_{ijt} is the revenue share of firm i in industry j at time t.

3 Estimation bias from omitted price heterogeneity

3.1 Output price bias

The omission of firms' outputs and prices can lead to a bias estimation of Eq. (9) (Klette and Griliches,1996; Melitz, 2000). Following Garcia-Marin and Voigtländer (2019), we define TFPR*, which now incorporates output prices and differs from the unadjusted version of revenue-based TFPR, defined earlier):

$$\Psi_{ijt}^{*} = \left(\Lambda_{ijt} Q_{ijt} P_{ijt}\right)^{\frac{\eta-1}{\eta}} \left(\frac{R_{jt}}{P_{jt}}\right)^{\frac{1}{\eta}}. \quad (19)$$

where P_{ijt} is the firm-level output price omitted from our previous set-up. Repeating the exercise through equation (4) to equation (6), we can again obtain:

$$r_{ijt} - p_{jt} = \frac{1}{\eta}\left(r_{jt} - p_{jt}\right) + \frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_k}{\eta} k_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt} + \frac{\eta-1}{\eta}\left(\lambda_{ijt} + \omega_{ijt} + p_{ijt}\right), \quad (20)$$

and so TFPR* is then:

$$\Psi_{ijt}^{*} = +\frac{1}{\eta}\left(r_{jt} - p_{jt}\right) = r_{ijt} - p_{jt} - \left(\frac{(\eta-1)\beta_l}{\eta} l_{ijt} + \frac{(\eta-1)\beta_k}{\eta} k_{ijt} + \frac{(\eta-1)\beta_m}{\eta} m_{ijt}\right), \quad (21)$$

which demonstrates how $\beta_l, \beta_k, \beta_m$ and elasticity of substitution η are potentially biased because revenue-based estimation would combine both quantity and price effects. If a firm i's efficiency improvements lead to changes in output prices, the standard TFPR estimate will be further biased. For example, if i operates under a downward-sloping demand curve, greater efficiency results in lower prices to drive higher sales, distorting the relationship between revenue and productivity. Our derivation indicates a negative correlation between $\left(\lambda_{ijt} + \varpi_{ijt} + p_{ijt}\right)$, but a positive correlation between Ψ_{ijt} and p_{ijt}. This implies that TFPR underestimates firm i's' physical efficiency, even when revenues are deflated by industry price indexes (Garcia-Marin and Voigtländer, 2019). The omission of output prices highlighted above also leads to biased markups due to biased estimates of elasticity substitution η and input elasticities.

From Eq. (21), we can similarly derive TFPQ** (which, unlike TFPQ* earlier, takes account of firm-level price differences) as:

$$(\lambda_{ijt} + \omega_{ijt})^{**} = \frac{\eta}{\eta - 1} \frac{\Psi^{*}_{ijt}}{p_{ijt}} - \frac{1}{\eta - 1}(r_{jt} - p_{jt}) \frac{1}{p_{ijt}}. \quad (22)$$

The equation demonstrates that output prices affect TFPQ** positively; the Ψ^{*}_{ijt} term is now multiplied by a fraction of the price term $1/p_{ijt}$, and the industry-level revenue term is also multiplied by a fraction of the price term $1/p_{ijt}$. Omitting firm-level prices will therefore lead to downward biased markup estimates.

3.2 Input price bias

Thus far, the derivation of (10) and (21) rely on expenditures for all inputs, rather than the actual quantities of inputs. Since input demand is inherently influenced by input prices, using expenditures introduces another potential source of bias in the estimation of the revenue function if the pass-through of input prices to output prices is incomplete (De Loecker et al., 2016).[3] It is, therefore, crucial to consider unobserved firm-specific input price variation, especially since only input expenditures—an issue common to firm-level productivity studies—are available. Although input prices cannot be directly observed, we can infer input 'quality' since firm i producing higher-quality products typically uses more expensive inputs (Kugler and Verhoogen, 2012). We address unobserved input prices by estimating the following equation to account for input quality (De Loecker et al. 2016),:

$$\boldsymbol{\tau}^{\chi}_{ijt} = \tau_t(p_{ijt}, s_{ijt}, Exp_{ijt}, G_{ijt}, F_{ijt}), \quad (23)$$

where $\boldsymbol{\tau}^{\chi}_{ijt}$ is a vector of inputs (i.e., $\chi = l, k, m$) expressed as function of other observable covariates included in $\tau_t(.)$. The elements in $\tau_t(.)$ Include: p_{ijt}, the output unit-value, assumed to be positively correlated with high input price and high input quality; s_{ijt} the firm i's market share; Exp_{ijt}, the firm i's export statusy; G_{ijt}, firm i's location (i.e., city, province); and F_{ijt}, firm

[3] De Loecker and Syverson (2021) also highlight potential variations in variable inputs. For example, differences in worker quality present a significant challenge in accurately measuring labour inputs, alongside unavailable intermediate quantities and prices, and the capital measure, which is prone to mismeasurement. These issues in input measurement further bias productivity estimates.

i's foreign investment status (i.e., the amount of foreign funds received by the firm), as foreign subsidiaries are more likely to use high quality input and face high input prices. In other words, (23) controls for unobserved input price variation across firms using data on observables.

Substituting Eq. (23) into the expression for input expenditures on labour, capital, and materials in Eq. (9); we get

$$r_{ijt} - p_{jt} = \frac{1}{\eta}\left(r_{jt} - p_{jt}\right) + \frac{(\eta-1)\beta_l}{\eta}\tilde{l}_{ijt} + \frac{(\eta-1)\beta_k}{\eta}\tilde{k}_{ijt} + \frac{(\eta-1)\beta_m}{\eta}\widetilde{m}_{ijt} + \frac{\eta-1}{\eta}\left(\lambda_{ijt} + \omega_{ijt} + p_{ijt}\right), \tag{24}$$

where $\tilde{l}_{ijt} = l^c_{ijt} \times \tau_t\left(p_{ijt}, s_{ijt}, Exp_{ijt}, G_{ijt}, F_{ijt}\right)$, $\tilde{k}_{ijt} = k^c_{ijt} \times \tau_t\left(p_{ijt}, s_{ijt}, Exp_{ijt}, G_{ijt}, F_{ijt}\right)$,, and $\widetilde{m}_{ijt} = m^c_{ijt} \times \tau_t\left(p_{ijt}, s_{ijt}, Exp_{ijt}, G_{ijt}, F_{ijt}\right)$. We use the notation l^c_{ijt}, k^c_{ijt}, and m^c_{ijt} to note that the input price correction term $\tau(\cdot)$ also enters by itself, i.e., $l^c_{ijt} = 1, l_{ijt}$, $k^c_{ijt} = 1, k_{ijt}$, and $m^c_{ijt} = 1, m_{ijt}$. We can then write the natural log of TFPR** as:

$$\begin{aligned}\Psi^{*\prime}_{ijt} &= \frac{\eta-1}{\eta}\left(\lambda_{ijt} + \varpi_{ijt} + p_{ijt}\right) + \frac{1}{\eta}\left(r_{jt} - p_{jt}\right) \\ &= r_{ijt} - p_{jt} - \left(\frac{(\eta-1)\beta_l}{\eta}\tilde{l}_{ijt} + \frac{(\eta-1)\beta_k}{\eta}\tilde{k}_{ijt} + \frac{(\eta-1)\beta_m}{\eta}\widetilde{m}_{ijt}\right), \end{aligned} \tag{25}$$

Furthermore, the TFPQ*** (which includes product quality, technical efficiency, and price components) can be backed out as:

$$\left(\lambda_{ijt} + \omega_{ijt}\right)^{**\prime} = \frac{\eta}{\eta-1}\frac{\Psi^*_{ijt}}{p_{ijt}} - \frac{1}{\eta-1}\left(r_{jt} - p_{jt}\right)\frac{1}{p_{ijt}}. \tag{26}$$

Further with both input and output prices taken into account, we label revenue and quality adjusted TFP as TFPR** and TFPQ***. We similarly relabel markup estimates as μ^{**} when taking into account price heterogeneity.

3.3 Econometric estimation

The parameters of interest include the elasticity of substitution $1/\eta$, revenue elasticity ($\frac{(\eta-1)\beta_l}{\eta}$, $\frac{(\eta-1)\beta_k}{\eta}$, $\frac{(\eta-1)\beta_m}{\eta}$), implied output elasticity ($\beta_l, \beta_k, \beta_m$), and firm-level TFP and markup measures. To obtain these estimates, we closely follow Blundell and Bond (1998) and Blundell and Bond (2000), which account for adjustment costs in all inputs and serially correlated productivity shocks (i.e., $\lambda_{ijt} + \varpi_{ijt}$) following an AR(1) process, as well as unobserved heterogeneity in $\lambda_{ijt} + \varpi_{ijt}$ across firms. In addition to adjustment costs, we allow input choices to respond to contemporaneous productivity shocks. This introduces the common challenges of unobserved heterogeneity and simultaneity in estimating the revenue function (Griliches and Mairesse, 1995). Beginning with a specification that addresses both corrections, let's set $\pi_{ijt} = \frac{\eta_j - 1}{\eta_j}\left(\lambda_{ijt} + \omega_{ijt} + p_{ijt}\right)$ and assume

$$\pi_{ijt} = \pi_{it} + v_{ijt}, \tag{27}$$

and

$$v_{ijt} = \rho_j v_{ij(t-1)} + \xi_{ijt}. \tag{28}$$

where ξ_{ijt} is a zero mean random shock that is potentially correlated with input choices, and we assume $0 < |\rho_j| < 1$. Lagging (24) (but with both price corrections implemented) by one period, multiplying the resulting equation through by ρ_j, and subtracting the result from (24), gives the quasi-differenced equation:

$$\begin{aligned} r_{ijt} - p_{jt} = {} & \rho_j\left(r_{ij(t-1)} - p_{j(t-1)}\right) + \frac{1}{\eta_j}\left(r_{jt} - p_{jt}\right) - \rho_j\left(r_{j(t-1)} - p_{j(t-1)}\right) \\ & + \frac{(\eta-1)\beta_l}{\eta}\left(\tilde{l}_{ijt} - \rho_j \tilde{l}_{ij(t-1)}\right) + \frac{(\eta-1)\beta_k}{\eta}\left(\tilde{k}_{ijt} - \rho_j \tilde{k}_{ij(t-1)}\right) \\ & + \frac{(\eta-1)\beta_m}{\eta}\left(\widetilde{m}_{ijt} - \rho_j m_{ij(t-1)}\right) + \left(1-\rho_j\right)\pi_{ijt} + \xi_{ijt}, \end{aligned} \tag{29}$$

The firm fixed effect (name the term here) creates a correlation between the lagged dependent variable and the error term ξ_{ijt} (Nickell, 1981). Additionally, input variables in the revenue equation become correlated with the error term (add the term here) due to immediate input responses to productivity shocks. One way to estimate Eq. (32) consistently is by using first differences and instrumental variables for potentially endogenous right-hand-side variables. Blundell and Bond (1998) and Blundell and Bond (2000) propose mild initial conditions that allow lagged levels of endogenous variables to serve as valid instruments for first differences. However, they also find that these lagged levels can be weak instruments in production function estimation. As an alternative, they recommend using System GMM, which estimates the model in both first differences and levels. Under certain conditions, lagged first differences can act as valid instruments for the levels equation, and System GMM offers more efficient estimates than a single-equation approach. We use this method to estimate the parameters of the revenue function.

4. Data

We use a comprehensive dataset obtained from the National Bureau of Statistics of China (NBSC). This dataset provides detailed information on over 50,000 Chinese manufacturing firms with annual sales greater than five million RMB from 1998 to 2007.

We follow the standard approach in the literature, such as Cai and Liu (2009), Brandt, Van Biesebroeck, and Zhang (2012), Feenstra, Li, and Yu (2014), and Wang and Wang (2015), to construct a consistent firm-level panel. First, we classify sectors based on the 2-digit Chinese industry code and exclude non-manufacturing firms. Firms in handicraft and 'other' manufacturing industries are also excluded due to their limited number from 2002 onwards, which could introduce measurement issues when calculating long-run productivity changes. Additionally, we retain only firms with positive employment and capital. As a result, we identify firms across 28 sectors.[4]

[4] Processing of Foods (13), Foods (14), Beverages (15), Tobacco (16), Textiles (17), Apparel, Footwear, Caps (18), Leather, Fur, Feather (19), Wood Products (20), Furniture (21), Paper Products (22), Printing & Reproduction (23), Articles for Culture, Education, and Sport (24), Petroleum, Coking, Fuel (25), Raw Chemicals (26), Medicines (27), Chemical Fibers (28), Rubber (29), Plastics (30), Non-metallic Minerals (31), Pressing of Ferrous Metals (32), Pressing of Non-ferrous Metals (33), Metal Products (34), General Machinery (35), Special Machinery (36), Transport Equipment (37), Electrical Machinery (39), Computers (40), and Measuring Instruments (41)

For the geographical analysis, we identified 412 cities across 31 provinces.[5] As illustrated in Figure 1, there are significant differences across firms' locations, with a relatively large concentration of firms in Guangdong (68,782 firms), Jiangsu (71,456 firms), Shanghai (27,743 firms), and Zhejiang (75,466 firms). These locational disparities are considered when examining firms' input quality, as firms in different locations are likely to face varying prices and quality of inputs.

Moreover, we use a two-digit industry price index deflator provided by Brandt et al. (2012) to adjust the nominal value of firms' output and revenue, and a province-specific fixed asset investment price index from the *China Statistical Yearbook (1998-2007)* to calculate the real value of the capital variable (De Loecker and Warzynski, 2012). We then employ the available firm-level total output data, along with deflated revenue data, to derive a firm-level price proxy.

Overall, we have data on 550,397 firms (based on 2,047,401 observations) over the period 1998-2007, with firms being observed in the dataset for an average of 5.6 years. Among these firms, 6.29% are observed for only 1 year, 8.47% for 2 years, 9.88% for 3 years, 18.86% for 4 years, 9.83% for 5 years, 10.09% for 6 years, 8.44% for 7 years, 5.34% for 8 years, 4.78% for 9 years, and 18.02% for the entire period. This structure results in an unbalanced panel of firms.

The mean revenue of firms in the sample is just over 72 million RMB, with total output exceeding 74 million RMB, and the average unit value is approximately 1.015 RMB. Figure 2 illustrates the changes in differential unit values (prices) across Chinese 2-digit industries during the period 1998-2007. For instance, the 'Tobacco' industry experienced a rise of approximately 5 percentage points between 1998 and 2004, while prices in the 'Metal Products,' 'Pressing Non-Ferrous,' and 'Chemical Fibers' industries remained flat over time. In contrast, industries such as 'Wood Products,' 'Computers,' 'Rubber,' and 'Non-metallic Minerals' saw prices fluctuate dramatically, with changes exceeding 10 percentage points. Additionally, about 27% of firms are active in the export market, although individual market shares remained small throughout the 1998-2007 period. We provide the summary statistics in Table 1.

[5] Xinjiang, Xizang (Tibet), Inner Mongolia, Gansu, Yunnan, Heilongjiang, Jilin, Liaoning, Guangdong, Hainan, Fujian, Zhejiang, Shanghai, Jiangsu, Shandong, Hebei, Tianjin, the Paracel Islands, Beijing, Sichuan, Chongqing, Guizhou, Hunan, Ningxia, Shaanxi, Qinghai, Shanxi, Jiangxi, Henan, Hubei, and Anhui.

5. Results

5.1 Implied output elasticity

We start by examining how output price heterogeneity potentially affects the revenue function and thus the estimated elasticities. Table 2 shows the results estimating the revenue function for 2-digit manufacturing industries from our structural model *without* incorporating firm-level prices; we provide revenue (columns 2-4) and implied output (columns 5-7) elasticities throughout the table. Table 2 also records the coefficient on the deflated industry revenue variable (column 1), where the inverse of the coefficient provides an estimate of the demand-side elasticity of substitution in the industry. We present both the average and standard deviation of the elasticities across sectors, and the final column (Column 8) reports the returns to scale. It is notable that a few sectors appear to have increasing returns to scale; for instance, processing of foods (2-digit 13), beverages (2-digit 15), textile (2-digit 17), printing and reproduction (2-digit 23), raw chemicals (2-digit 26), medicines (2-digit 27), and electrical machinery (2-digit 39), all with estimates of the industry-average returns to scale exceeding 1. While it is possible for many firms in a sector to exhibit increasing returns to scale, the estimate of the industry-average returns to scale is close to 1 for most firms/sectors.

Table 3 repeats our revenue function estimation, incorporating both input and output prices at firm level.[6] These yields more plausible results for revenue, implied output, and return to scale estimates. For example, the revenue, output elasticities, and returns to scale are slightly smaller than those provided by Table 2; sectors 13 (processing of food) and 17 (textiles) are now identified as having close to constant returns to scale (0.916 and 0.992), with both revenue and implied output elasticities lower than those reported in Table 2. These results consider the potential correlation between output prices and $TFPQ^{**}$, as well as the introduction of price heterogeneity into our revenue production framework.

To further emphasize the impact of omitting rather than accounting of firm-level price differences in these estimated parameters, we present two density distributions of the implied output elasticities under the two specifications in Figure 3. The sum of the implied output elasticities without considering output price variation has an average value of 0.98 (blue), while

[6] We provide results for input and output, respectively, price corrections separately in our online appendix V. We also provide results using alternative methods; production approach and cost-share approach. Please see our online appendix for more details.

the sum of the implied output elasticities with both output and input prices taken into account has a mean of 0.77 (black). The sum of implied output elasticities with price differences incorporated demonstrates a considerable dispersion that reflects the variation introduced by price differences in our demand elasticity estimates, indicating potential bias arising from variation in input and output prices. This finding aligns with the observations of Blackwood et al. (2021); appropriate caution is needed when interpreting results using revenue data when firms' price information is missing.

5.2 TFP and markup estimates

We present the estimates of levels of TFP and markups estimates in Table 4. The standard specification underestimates TFPR, TFPQ, and markups on average. As Table 4 shows, without adjusting for output price heterogeneity, the estimates for TFPR (Ψ_{it}), TFPQ* ($\lambda_{it} + \omega_{it}$), and markups ($\mu$) are lower than for the estimates taking the firm-level differences into account. When the heterogeneity among firms in terms of input prices is also accounted for, the estimates increase again. When both output and input prices are included, the estimates rise from 1.274 to 2.712 for TFPR*, from 1.373 to 3.633 for TFPQ***, and from 1.066 to 1.201 for markups (μ^{**}).

We also plot the distribution of TFP and markups across manufacturing firms in Figures 4 and 5; Panel A of Figure 4 shows the revenue-based TFP (TFPR), Panel B of Figure 4 shows the quality-adjusted TFP (TFPQ), and Figure 5 the markups (μ). In each, the gray line shows results for the specification without controlling for price heterogeneity, and the black line the estimates with both input and output price controlled for. The estimates of both TFPR and TFPQ with using firm-level output and input prices are higher and more dispersed than the estimates without taking into account price heterogeneity. Similarly, markup estimates with price heterogeneity taken into account are higher and more dispersed than estimates without incorporating price heterogeneity.

The standard deviation of both sets of alternative estimates is thus more dispersed than the standard baseline, reflecting greater variability in firm performance once price heterogeneity is accounted for. This result implies not only a risk of underestimating the true levels of TFP and markups but also of obscuring the extent of variability across firms.

5.3 TFP and Markups Growth: within-firm Change, Reallocation and Net Entry

To show the size of potential bias arising from input and output prices heterogeneity, we compare results with and without firm-level prices to show in the standard approach. Specifically, we consider how within-firm, across-firms reallocation, and aggregate TFP growth patterns are affected by omitting input and output price changes. Following De Loecker et al. (2020), and Coyle et al. (2024), we estimate the following equation:

$$\Delta x_t = \underbrace{\sum_i \Delta x_{it} s_{it-1}}_{Within} + \underbrace{\sum_i \tilde{x}_{it-1} \Delta s_{it} + \sum_i \Delta x_{it} \Delta s_{it}}_{Reallocation} + \underbrace{\sum_{i \in Entry} \tilde{x}_{it} \Delta s_{it} - \sum_{i \in Exit} \tilde{x}_{it-1} \Delta s_{it-1}}_{Net\ Entry}, \tag{30}$$

where $\tilde{x}_{it} = x_{it} - x_{t-1}$ and $\tilde{x}_{it-1} = x_{it-1} - x_{t-1}$ are set to de-mean productivity by the appropriate aggregate (share-weighted) level in order to identify correctly the role of the reallocation term (Farber, Haltiwanger, and Abraham, 1997; De Loecker et al., 2020). The first term on the right, $\sum_i \Delta x_{it} s_{it-1}$, refers to the within-firm productivity improvement that contributes to the aggregate growth rate Δx_t. The second and third terms, $\sum_i \tilde{x}_{it-1} \Delta s_{it} + \sum_i \Delta x_{it} \Delta s_{it}$, then capture reallocation effects between firms in the industry. The last two terms refer to the effects of firm entry and exit into the economy or sector. We set each term as an index to 1 in the first year of the sample (i.e., 1998). We then accumulate the relevant term forward to track the evolution of the index level through within-firm, reallocation, and net entry effects over the sample.

Figure 6 presents the decomposition results for revenue-weighted revenue-based TFP and quality-based TFP, both with and without incorporating price heterogeneity. Figure 7 does the same for estimated markups. By the end of the 10-year period, both the growth of revenue-based TFP (Panel A of Figure 6) and quality-adjusted TFP (Panel C of Figure 6) were more than 10 percent higher when price heterogeneity is not controlled for. By contrast, when input and output price differences among firms are accounted for, the upward trends for $TFPR^{**}$ (black line in Panel B of Figure 6) and $TFPQ^{***}$ (black line in Panel D of Figure 6) are steeper than those without price corrections, with both measures showing increases exceeding 20 percent. This difference is primarily driven by within-firm effects (represented by black dots) across industries. The within-firm term increases by more than 10% for both measures when price heterogeneity is controlled for, compared to a relatively flat trend over 1998–2007 when price heterogeneity is not accounted for. The reallocation term also shows variation, with an overall increase of more than 25% when price corrections are applied, compared to an increase of approximately 20% without price adjustments. Lastly, the net entry term reveals a significant decline, decreasing by over 10% after 2001 in both adjusted and unadjusted figures.

The aggregate markup trends also differ depending on whether price heterogeneity is implemented. When it is not taken into account, Panel A of Figure 7 indicates a relatively stable markup trend over the 10-year period. However, once price heterogeneity is taken into account, Panel B of Figure 7 reveals a declining markup trend between 1998 and 2007, with markups falling by more than 0.2 percentage points.

The concept of net entry warrants particular attention. The existing literature highlights exit and survival as a critical nexus of productivity growth: firms with lower productivity are less likely to survive and prosper compared to their more efficient counterparts, resulting in selection-driven increases in aggregate industry productivity (Foster, Haltiwanger, and Syverson, 2008). Without incorporating price heterogeneity (Panels A and C of Figure 6), the net entry term appears modest, decreasing by approximately 6–7% by the end of 2007. However, when taking it into account (Panels B and D of Figure 6), the net entry rate declines significantly, nearly twice as fast at 12–13%. Similarly, the net entry term is estimated as positive for markups (around 0.1%) for the period 1998–2007 when price variations are ignored (Panels A of Figure 7), whereas it turns negative (approximately -0.1%) when prices are accounted for (Panels B of Figure 7).

Figure 8 plots the entry and exit terms separately. Panels A and B reveal that the contribution of new entrants to TFP growth is substantially lower during the later years 2003–2007 when firm-level prices are considered, compared to when they are omitted. In contrast, Figure 9 shows an opposing pattern for markups, where price corrections indicate a stronger role for new entrants. These findings suggest that firm-level price heterogeneity has a pronounced impact on firm performance, particularly from the demand side, as suggested by Klette and Griliches (1996). This heterogeneity influences not only firm survival but also entry decisions, thereby shaping aggregate productivity dynamics (Foster et al., 2008).[7]

[7] It is important to note that different decomposition methods, which involve varying weighting matrices, can influence the results (see Foster, Haltiwanger, and Krizan, 2001). Given that our focus here is to

5.4 Price heterogeneity through time – the size of the potential bias

Raval (2024) emphasizes that the time path in estimated markups under different inputs and estimation approaches should be the same. However, this analysis, based on a simple specification regressing firm-level markups on time and industry fixed effects, reveals that markup estimates vary depending on the variable inputs selected, exhibiting greater dispersion and even opposite time trends. In addition, as demonstrated by Melitz (2000), the time path of aggregate productivity reflects dynamic changes in quality in the economy. To quantify the biases in our sample and the observed trends from omitting price heterogeneity, we follow the existing studies(Specific Ref needed here, otherwise delete the " we follow the existing studies"), isolating the differences between estimates with and without prices controls. We estimate the following specification:

$$lnX'_{ijt} = \alpha + \gamma_t + \delta_j + \varepsilon_{it} \tag{31}$$

where $lnX'_{ijt} = TFPR, TFPQ *, \mu$. We include time dummies γ_t, with the year 1998 set to zero as the reference year and δ_j, which refers to industry fixed effects.

Figures 10 and 11 illustrate the aggregate productivity and markup measures, along with their associated biases, under various scenarios. Figure 10 presents TFPR (Panel A) and TFPQ (Panel B) estimates under four cases : without price heterogeneity corrections; with output price corrections; with input price corrections; and with both input and output price corrections. Similarly, Figure 11 illustrates these corrections for markup estimates. All figures are normalized to zero, with1998 as the reference year.

TFPR in Figure 10 (Panel A) indicates a relatively flat trend from 2004 to 2007 when price biases are not addressed. In contrast, TFPQ (Panel B) shows a markedly steeper upward trajectory when price biases are corrected. The additional control for input and output price variations reveals

examine how price heterogeneity affects growth patterns alongside firms' entry and exit, the dynamic Olley-Pakes decomposition (DOPD) introduced by Melitz and Polanec (2015) is particularly well-suited as an additional robustness check. If price heterogeneity indeed influences productivity measures, we would expect the growth dynamics of the entrant component to reflect this impact too. Figure 8 in Appendix I provides further evidence on this point; the results align with our earlier findings, showing a persistently negative contribution from entrant firms, particularly pronounced in 2004. See Appendix I for more details.

the most substantial upward trend, with differences ($\Psi^{**} - \Psi$ and $(\lambda + \omega)^{***} - (\lambda + \omega)^{*}$, red charts) reflecting potential biases (i.e., underestimation in Ψ and $(\lambda + \omega)^{*}$) between the estimates. Figure 11 presents the markup estimates, showing a sharper declining trend during 1998–2004 when price corrections are applied. The highlighted biases ($\mu^{**} - \mu$, red charts) suggest significant overestimation of the true changes in markups when price heterogeneity is not accounted for. Moreover, the biases increase significantly over time, with the largest discrepancies observed in 2007. The increasing bias, positive in TFP and negative in markups, underscores the critical role of price heterogeneity in accurately capturing aggregate productivity and markup dynamics.

6. Conclusion

This paper examines the role of output and input price adjustments in the estimation of TFP and markups during China's rapid economic growth from 1998 to 2007. We take advantage of detailed firm-level data on total revenue and quantities sold to estimate TFP and markups using a structural approach. Our methodology relies on several key assumptions, including Cobb-Douglas firm-level production functions with heterogeneous Hicks-neutral technical efficiency. To account for market structure, we impose Cournot competition rather than simple monopolistic competition, ensuring that markups remain time-varying. We estimate markups using firms' market shares and the elasticity of industry revenue.

While these assumptions are strong, we follow the pioneered methods of Klette and Griliches (1996) and Melitz (2000), later extended by Coyle et al. (2024), to recover TFP and markups under these conditions. Within this framework, we incorporate firm-level output unit-values as proxies for firm-level output prices and use firm-specific information – such as market share, export status, location, and foreign investment status – to estimate input quality. This is particularly important in our context since we want to analyse how price biases affect TFP and markups. An additional advantage of our approach is that, since we observe firm-level output unit-values in the data, we can directly correct for revenue function distortions and impose input quality adjustments to obtain more accurate firm-level TFP and markup estimates and therefore carry out the counterfactual exercise.

We show that failing to account for firm-level price heterogeneity introduces biases in TFP and markup estimates. Using a structural approach to establish baseline TFP and markup estimates, we highlight both the direction and magnitude of these biases. For both TFP measures (revenue-based and quality-adjusted), the baseline levels and growth estimates are lower in the standard approach compared to those obtained when accounting for price heterogeneity. For markup measures, we find that levels are substantially underestimated and appear relatively more "constant" when price heterogeneity is not taken into account.

Our results provide reason for caution in drawing conclusions about firm level and aggregate productivity performance and have broader implications for thinking about the price heterogeneity, TFP, markups, and resource misallocation across firms in developing countries. Our approach produces measures of quality- and revenue-based TFP and markups with and without price heterogeneity taken into account. Our comparison indicates that price heterogeneity not only affects TFP and markups but also distorts firms' market entry during China's rapid growth period. Hsieh and Klenow (2009) define revenue-based TFP as TFP multiplied by price and discuss the potential impact of resource misallocation on the marginal products of capital and labour and show how revenue-based TFP is potentially determined by the misallocation. Autor et al. (2020) and Goodridge, Haskel, and Wallis (2013, 2018), furthermore, have emphasised the importance of factors such as intangible capital and fixed component in labour cost both of which are closely linked to resource allocation and firm performance. Crucially, our approach can deliver measures of both TFP and markups with price heterogeneity addressed across firms, which potentially further improves upon our understanding of the role of misallocation associated with capital and labour in generating productivity dispersion. We leave the analysis of the role of resource allocation on the distribution of these performance measures for future research.

All tables and graphs

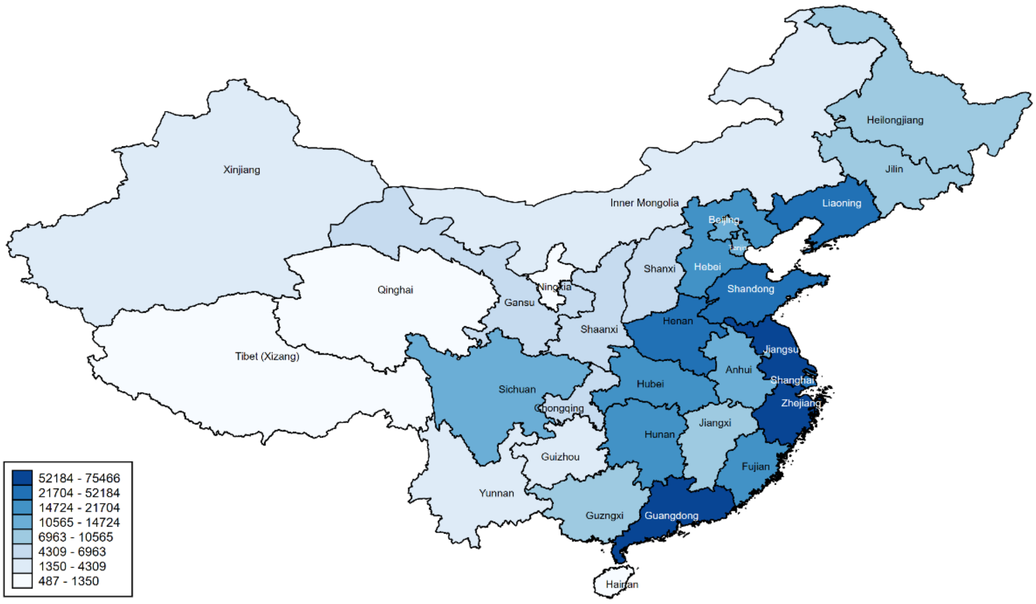

Figure 1. Heterogeneity in Firm Location 1998-2007 through Provinces/Cities

Notes: The figure plots the distribution of number of firms located through each provinces/cities.

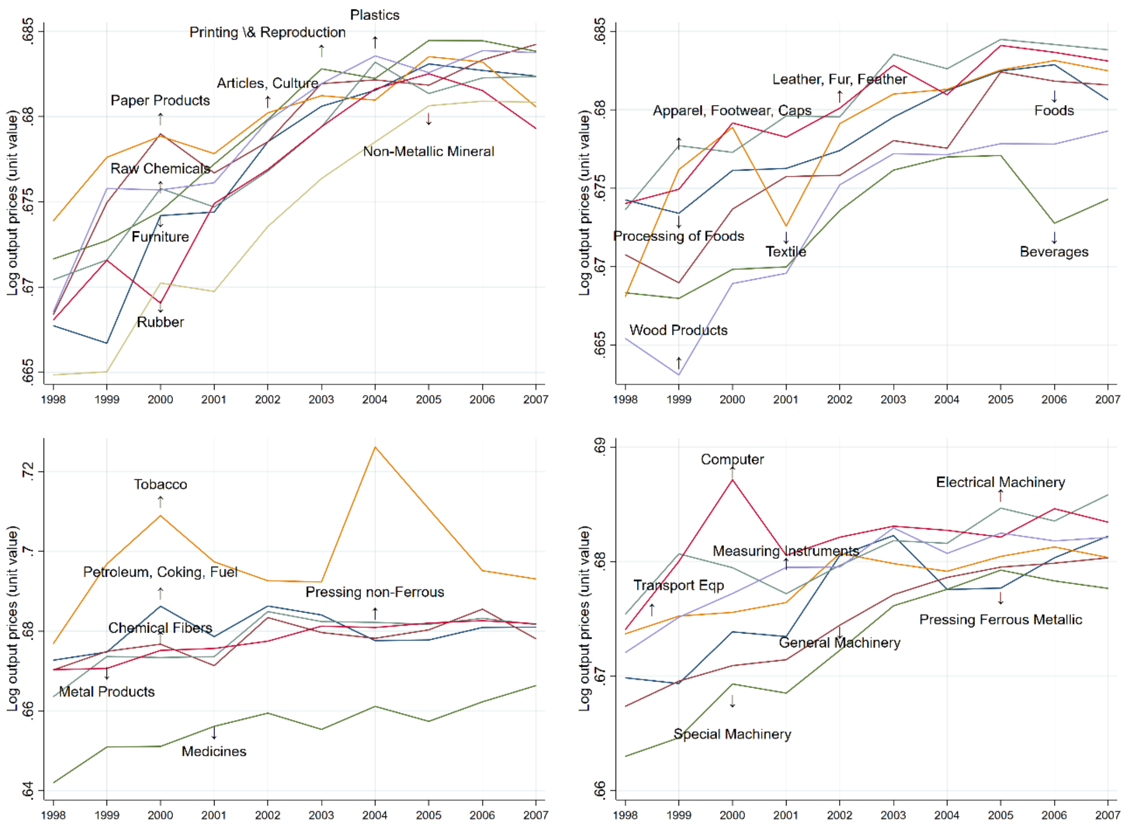

Figure 2. Price Heterogeneity through 2-digit Sectors

Notes: The figure plots the distribution of price heterogeneity through each 2-digit sector 1998-2007.

Table 1. Summary Statistics (firm-level average)

	Mean	Std.	Observations
	(1)	(2)	(3)
Total output	74,625.35	653,948.7	2,045,233
Revenue	72,976.37	646,964.6	2,045,233
Unit value (price)	1.015	23.940	2,045,233
Revenue (in log)	9.728	1.910	2,045,233
Wages (in log)	6.919	1.600	2,045,233
Capital (in log)	8.533	1.973	2,045,233
Materials (in log)	9.333	1.914	2,045,233
Price (in log)	0.678	0.089	2,045,233
Foreign investment received (in log)	1.792	3.605	2,045,233
Export status (Dummy)	0.269	0.443	2,045,233
Market share (in log)	0.00014	0.0008	2,045,233

Notes: This table reports summary statistics through levels for all variables used in our structure approach and markup estimation. Regarding the variables used to estimate TFP and markups, the mean log values are as follows: wages at 6.92, capital stock at 8.53, materials at 9.33, and price at 0.678. For the variables used to proxy input quality, the data indicate that, on average, firms receive approximately 1.792 (in log) in investment from foreign multinationals.

Table 2. Revenue and Implied Output Elasticity

	Revenue Elasticity				Implied Output Elasticity			
	$1/\eta$	$(\eta-1/\eta)\beta_l$	$(\eta-1/\eta)\beta_k$	$(\eta-1/\eta)\beta_m$	β_l	β_k	β_m	RS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2-digit 13	0.030***	0.957***	-0.013*	0.031***	0.987	-0.013	0.028	1.002
(Processing of Foods)	(0.005)	(0.009)	(0.008)	(0.008)				
2-digit 14	0.016***	0.967***	-0.004	0.017**	0.983	-0.004	0.018	0.997
(Foods)	(0.007)	(0.013)	(0.008)	(0.008)				
2-digit 15	0.026***	0.972***	-0.014	0.022	0.999	0.010	0.022	1.031
(Beverages)	(0.009)	(0.021)	(0.012)	(0.014)				
2-digit 16	0.067	0.675***	-0.075	-0.223*	0.725	-0.080	-0.240	0.405
(Tobacco)	(0.052)	(0.082)	(0.113)	(0.134)				
2-digit 17	0.020***	0.903***	0.045***	0.054***	0.923	0.046	0.055	1.024
(Textile)	(0.006)	(0.012)	(0.009)	(0.009)				
2-digit 18	0.107***	0.784***	0.027***	0.075***	0.878	0.030	0.084	0.992
(Apparel, Footwear, Caps)	(0.012)	(0.016)	(0.011)	(0.009)				
2-digit 19	0.039***	0.873***	0.021***	0.065***	0.908	0.021	0.067	0.996
(Leather, Fur, Feather)	(0.010)	(0.020)	(0.009)	(0.011)				
2-digit 20	0.092***	0.590***	0.031*	0.179***	0.650	0.034	0.198	0.882
(Wood Products)	(0.017)	(0.034)	(0.018)	(0.029)				
2-digit 21	0.109***	0.715***	0.037*	0.074***	0.803	0.041	0.084	0.928
(Furniture)	(0.018)	(0.048)	(0.023)	(0.027)				
2-digit 22	0.052***	0.782***	0.029**	-0.008	0.825	0.031	0.130	0.986
(Paper Products)	(0.009)	(0.018)	(0.013)	(0.009)				
2-digit 23	0.078***	0.781***	0.040***	0.115***	0.847	0.043	0.125	1.015
(Printing \& Reproduction)	(0.014)	(0.021)	(0.015)	(0.017)				
2-digit 24	0.144***	0.673***	-0.013	0.111***	0.787	-0.016	0.130	0.901
(Articles, Culture)	(0.022)	(0.038)	(0.020)	(0.027)				
2-digit 25	0.077***	0.801***	-0.023	0.030	0.869	-0.025	0.032	0.876
(Petroleum, Coking, Fuel)	(0.022)	(0.044)	(0.037)	(0.025)				
2-digit 26	0.026***	0.942***	0.019***	0.036***	0.967	0.019	0.037	1.023
(Raw Chemicals)	(0.007)	(0.012)	(0.008)	(0.008)				
2-digit 27	0.063***	0.871***	-0.030***	0.078***	0.930	0.009	0.083	1.022
(Medicines)	(0.018)	(0.024)	(0.011)	(0.012)				
2-digit 28	0.023	0.879***	-0.001	0.043	0.900	-0.001	0.044	0.943
(Chemical Fibers)	(0.017)	(0.051)	(0.016)	(0.055)				
2-digit 29	0.047***	0.895***	-0.008	0.023	0.940	-0.009	0.025	0.956
(Rubber)	(0.013)	(0.032)	(0.018)	(0.019)				

(*continued*)

Table 2 (continued). Revenue and Implied Output Elasticity

	Revenue Elasticity				Implied Output Elasticity			
	$1/\eta$	$(\eta-1/\eta)\beta_l$	$(\eta-1/\eta)\beta_k$	$(\eta-1/\eta)\beta_m$	β_l	β_k	β_m	RS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2-digit 30	0.107***	0.729***	0.019	0.107***	0.816	0.022	0.120	0.958
(Plastics)	(0.011)	(0.018)	(0.013)	(0.010)				
2-digit 31	0.077***	0.768***	0.022***	0.131***	0.833	0.024	0.142	0.999
(Non-Metallic Mineral)	(0.009)	(0.012)	(0.007)	(0.008)				
2-digit 32	0.050***	0.993***	-0.026**	-0.025*	1.045	-0.028	-0.038	0.979
(Pressing Ferrous Metallic)	(0.013)	(0.022)	(0.011)	(0.014)				
2-digit 33	0.023	0.901***	0.048***	0.047***	0.923	0.049	0.048	0.924
(Pressing non-Ferrous)	(0.016)	(0.025)	(0.018)	(0.014)				
2-digit 34	0.069***	0.890***	0.007	-0.045***	0.957	0.008	-0.048	0.917
(Metal Products)	(0.013)	(0.030)	(0.018)	(0.013)				
2-digit 35	0.080***	0.751***	0.037***	0.108***	0.817	0.041	0.117	0.975
(General Machinery)	(0.007)	(0.018)	(0.008)	(0.009)				
2-digit 36	0.064***	0.785***	0.023*	0.124***	0.840	0.024	0.132	0.996
(Special Machinery)	(0.010)	(0.018)	(0.012)	(0.012)				
2-digit 37	0.054***	0.798***	0.033***	0.071***	0.844	0.035	0.075	0.954
(Transport Eqp)	(0.010)	(0.021)	(0.012)	(0.011)				
2-digit 39	0.069***	0.881***	0.024**	0.027***	0.947	0.026	0.029	1.002
(Electrical Machinery)	(0.011)	(0.022)	(0.012)	(0.011)				
2-digit 40	0.047***	0.802***	0.024	0.096***	0.843	0.025	0.101	0.969
(Computer)	(0.010)	(0.020)	(0.020)	(0.017)				
2-digit 41	0.055***	0.765***	-0.016	0.123***	0.809	-0.017	0.131	0.923
(Measuring Instruments)	(0.016)	(0.037)	(0.021)	(0.022)				

Notes: $1/\eta$ refers to industry deflated revenue elasticity. $(\eta-1/\eta)\beta_l$, $(\eta-1/\eta)\beta_k$, and $(\eta-1/\eta)\beta_m$ refer to revenue elasticity of labour, capital, and materials. β_l, β_k, and β_m refer to implied output elasticity of labour, capital, and materials. RS refers to return to scale (calculated as the sum of the output elasticities).

Table 3. Revenue and Implied Output Elasticity (with output and input price correction)

		Revenue Elasticity			Implied Output Elasticity			
	$1/\eta$	$(\eta-1/\eta)\beta_l$	$(\eta-1/\eta)\beta_k$	$(\eta-1/\eta)\beta_m$	β_l	β_k	β_m	RS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2-digit 13	0.160***	0.785***	-0.024*	-0.027***	0.936	-0.028	0.019	0.927
(Processing of Foods)	(0.008)	(0.014)	(0.008)	(0.007)				
2-digit 14	0.130***	0.788***	-0.009	0.0003	0.907	-0.010	0.0003	0.897
(Foods)	(0.014)	(0.023)	(0.010)	(0.009)				
2-digit 15	0.202***	0.696***	-0.022	0.001	0.873	-0.027	0.014	0.860
(Beverages)	(0.019)	(0.032)	(0.018)	(0.009)				
2-digit 16	0.184***	0.308***	-0.131	0.0007	0.378	-0.161	0.008	0.210
(Tobacco)	(0.038)	(0.081)	(0.082)	(0.060)				
2-digit 17	0.086***	0.854***	0.027***	0.047***	0.934	0.030	0.052	1.016
(Textile)	(0.009)	(0.013)	(0.008)	(0.006)				
2-digit 18	0.202***	0.736***	0.011	-0.027***	0.923	0.014	0.056	0.993
(Apparel, Footwear, Caps)	(0.013)	(0.018)	(0.014)	(0.007)				
2-digit 19	0.128***	0.804***	0.014***	0.055***	0.922	0.016	0.063	1.001
(Leather, Fur, Feather)	(0.014)	(0.018)	(0.009)	(0.009)				
2-digit 20	0.270***	0.483***	-0.007	-0.043***	0.663	-0.010	0.104	0.757
(Wood Products)	(0.016)	(0.028)	(0.013)	(0.013)				
2-digit 21	0.215***	0.615***	0.006	0.003	0.784	0.008	0.062	0.854
(Furniture)	(0.017)	(0.052)	(0.017)	(0.014)				
2-digit 22	0.227***	0.656***	-0.008	0.050***	0.848	-0.010	0.064	0.902
(Paper Products)	(0.015)	(0.026)	(0.013)	(0.009)				
2-digit 23	0.221***	0.615***	-0.002	0.013	0.790	-0.002	0.067	0.855
(Printing \& Reproduction)	(0.015)	(0.023)	(0.016)	(0.012)				
2-digit 24	0.235***	0.628***	-0.002	0.082***	0.822	-0.003	0.107	0.926
(Articles, Culture)	(0.019)	(0.035)	(0.020)	(0.018)				
2-digit 25	0.212***	0.612***	-0.031	0.005	0.779	-0.042	0.007	0.744
(Petroleum, Coking, Fuel)	(0.035)	(0.052)	(0.033)	(0.024)				
2-digit 26	0.121	0.809***	-0.0002	0.018***	0.921	-0.0003	0.021	0.941
(Raw Chemicals)	(0.009)	(0.016)	(0.007)	(0.006)				
2-digit 27	0.219***	0.664***	-0.023**	0.046***	0.850	-0.030	0.060	0.880
(Medicines)	(0.020)	(0.027)	(0.011)	(0.019)				
2-digit 28	0.090***	0.745***	-0.007	0.027	0.820	-0.008	0.029	0.841
(Chemical Fibers)	(0.016)	(0.059)	(0.021)	(0.045)				
2-digit 29	0.129***	0.760***	-0.008	-0.018	0.873	-0.009	0.020	0.848
(Rubber)	(0.020)	(0.043)	(0.016)	(0.012)				

(*continued*)

Table 3 (continued). Revenue and Implied Output Elasticity (with output and input price correction)

	Revenue Elasticity				Implied Output Elasticity			
	$1/\eta$	$(\eta-1/\eta)\beta_l$	$(\eta-1/\eta)\beta_k$	$(\eta-1/\eta)\beta_m$	β_l	β_k	β_m	RS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2-digit 30	0.207***	0.649***	0.017	0.065***	0.819	0.022	0.082	0.923
(Plastics)	(0.011)	(0.019)	(0.012)	(0.009)				
2-digit 31	0.185	0.665***	0.010*	0.061***	0.817	0.012	0.076	0.905
(Non-Metallic Mineral)	(0.010)	(0.017)	(0.006)	(0.006)				
2-digit 32	0.172***	0.744***	-0.015	0.0009	0.899	-0.018	0.001	0.882
(Pressing Ferrous Metallic)	(0.022)	(0.040)	(0.012)	(0.016)				
2-digit 33	0.061***	0.815***	0.023	-0.013	0.869	0.025	0.002	0.896
(Pressing non-Ferrous)	(0.020)	(0.033)	(0.016)	(0.007)				
2-digit 34	0.116***	0.800***	-0.021*	-0.033***	0.906	-0.024	-0.038	0.844
(Metal Products)	(0.019)	(0.037)	(0.013)	(0.011)				
2-digit 35	0.160***	0.671***	0.025***	0.072***	0.799	0.029	0.086	0.914
(General Machinery)	(0.009)	(0.020)	(0.007)	(0.006)				
2-digit 36	0.213***	0.659***	0.008	0.004	0.838	0.010	0.076	0.924
(Special Machinery)	(0.010)	(0.019)	(0.010)	(0.009)				
2-digit 37	0.203***	0.624***	0.002	0.068***	0.783	0.002	0.086	0.871
(Transport Eqp)	(0.014)	(0.032)	(0.012)	(0.012)				
2-digit 39	0.111***	0.763***	0.002	0.063***	0.859	0.002	0.071	0.932
(Electrical Machinery)	(0.012)	(0.019)	(0.012)	(0.014)				
2-digit 40	0.200***	0.576***	-0.010	0.086***	0.721	-0.013	0.108	0.816
(Computer)	(0.020)	(0.033)	(0.014)	(0.020)				
2-digit 41	0.239***	0.643***	-0.015	-0.004	0.845	-0.020	0.063	0.888
(Measuring Instruments)	(0.016)	(0.026)	(0.009)	(0.008)				

Notes: $1/\eta$ refers to industry deflated revenue elasticity. $(\eta-1/\eta)\beta_l$, $(\eta-1/\eta)\beta_k$, and $(\eta-1/\eta)\beta_m$ refer to revenue elasticity of labour, capital, and materials. β_l, β_k, and β_m refer to implied output elasticity of labour, capital, and materials. RS refers to return to scale (calculated as the sum of the output elasticities).

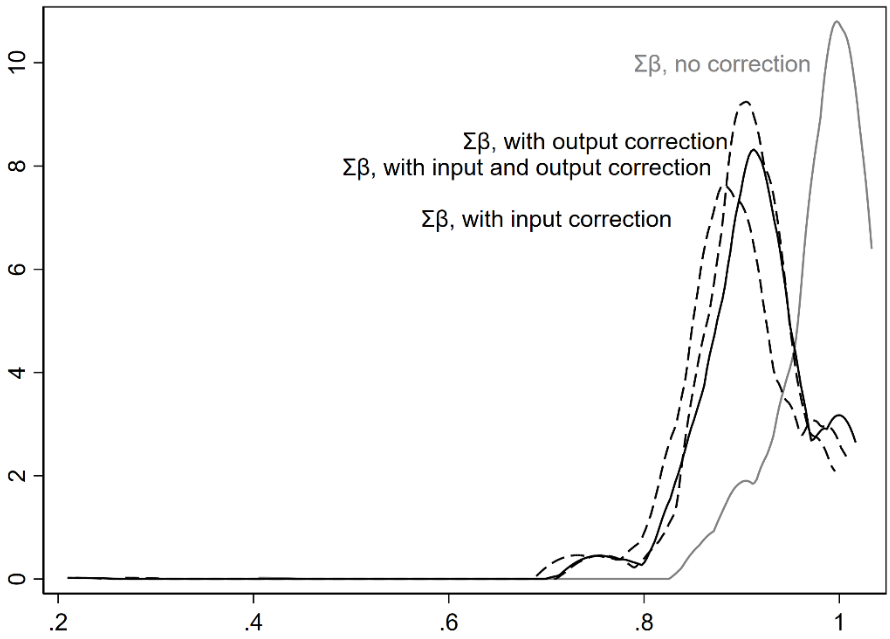

Figure 3. Cross-industry distribution of $\sum_j \beta_j$

Notes: β_j refers to the implied output elasticities (capital k, labour l, and material m) between specifications without and with output prices correction.

Table 4. TFP Estimates (firm-level average)

Variable	Methodology	Mean (1)	Std (2)
TFPR (without prices correction)	Ψ_{it}	1.274	0.893
TFPQ*(without prices correction)	$\lambda_{it}+\omega_{it}$	1.373	0.984
TFPR*(with output prices correction)	Ψ^*_{it}	2.712	1.066
TFPQ**(with output prices correction)	$(\lambda_{it}+\omega_{it})^{**}$	3.633	1.413
TFPR** (with input prices correction)	$\Psi^{*\prime}_{it}$	2.687	1.049
TFPQ**' (with input prices correction)	$(\lambda_{it}+\omega_{it})^{**\prime}$	3.179	1.355
TFPR**(with output & input prices correction)	Ψ^{**}_{it}	2.666	1.033
TFPQ***(with output & input prices correction)	$(\lambda_{it}+\omega_{it})^{***}$	2.835	1.260
μ (without price corrections)	$(1/1-s_{it})(\eta/\eta-1)$	1.066	0.034
μ^* (with output price corrections)	$(1/1-s_{it})(\eta/\eta-1)$	1.201	0.071
$\mu^{*\prime}$ (with input price corrections)	$(1/1-s_{it})(\eta/\eta-1)$	1.174	0.063
μ^{**} (with output & input prices corrections)	$(1/1-s_{it})(\eta/\eta-1)$	1.195	0.075

Notes: This table reports summary statistics through levels based on the 2,045,233 observations.

Panel A TFPR

Panel B TFPQ

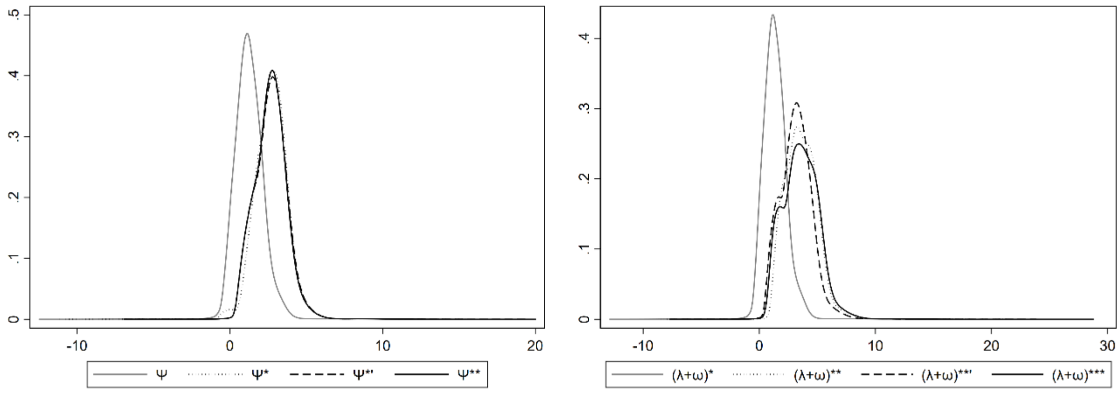

Figure 4. TFP Distribution

Notes: The figure plots the distribution of TFP measures through 1998-2007. Panel A presents the distribution of TFPR (Ψ without prices correction, Ψ^{*} with output prices correction, $\Psi^{*\prime}$ with input prices correction, and Ψ^{**} with input and output prices correction). Panel B presents the distribution of TFPQ ($(\lambda+\omega)^{*}$without prices correction, $(\lambda+\omega)^{**}$ with output prices correction, $(\lambda+\omega)^{**\prime}$ with input prices correction, and $(\lambda+\omega)^{***}$ with input and output prices correction).

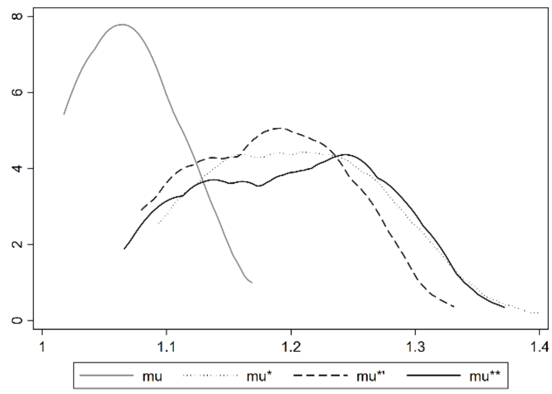

Figure 5. Markups Distribution

Notes: The figure plots the distribution of markups (μ without prices correction, μ^{*} with output prices correction, $\mu^{*\prime}$ with input prices correction, and μ^{**} with input and output prices correction).

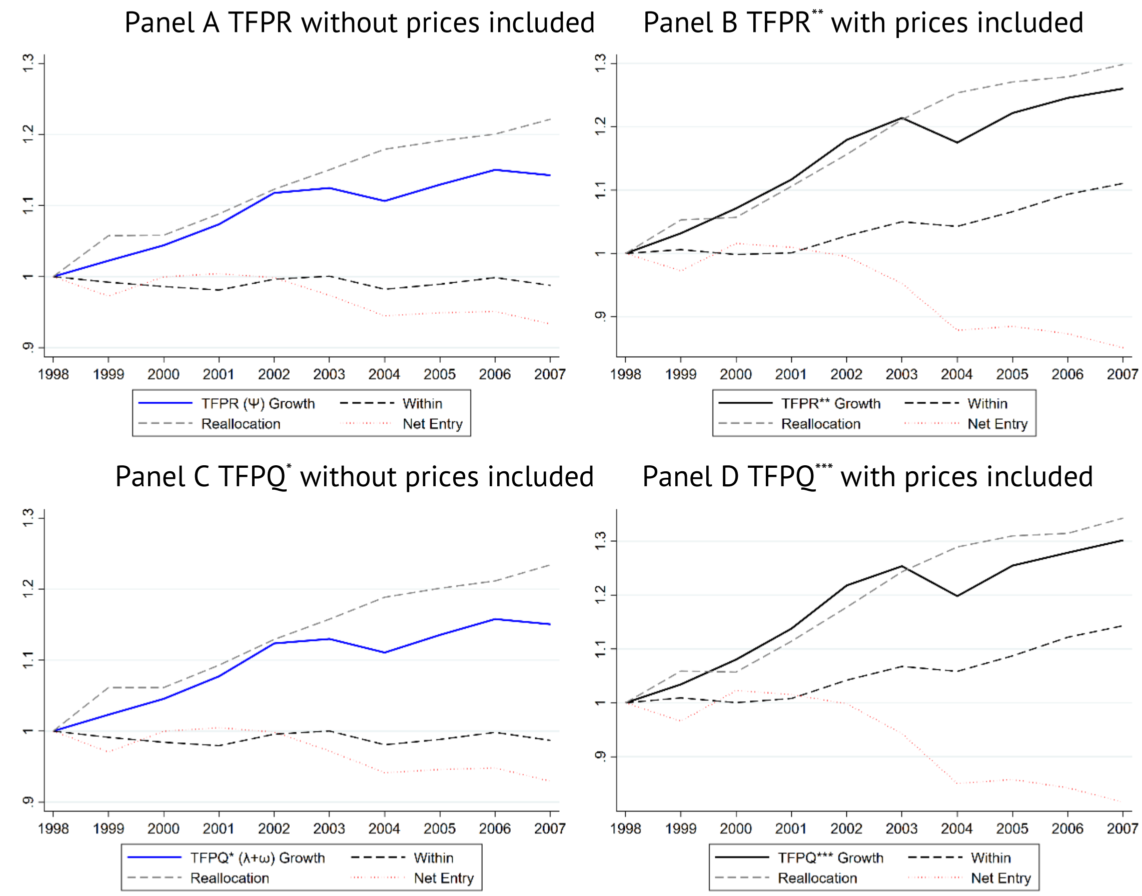

Figure 6. Cumulative Revenue-based TFP and Quality-adjusted TFP Growth

Notes: The figure plots the cumulative dynamic growth patterns of TFP measures from 1998 to 2007, with (Panels B and D) and without (Panels A and C) input and output price corrections. Panel A shows the aggregate growth of TFPR (Ψ without price corrections), Panel B displays the aggregate growth of TFPR** (Ψ^{**} with price corrections), Panel C presents estimates of TFPQ* ($(\lambda+\omega)^{*}$ without price corrections, and Panel D shows estimates of TFPQ*** ($(\lambda+\omega)^{***}$ with price corrections). The aggregate growth is set to 1 in 1998.

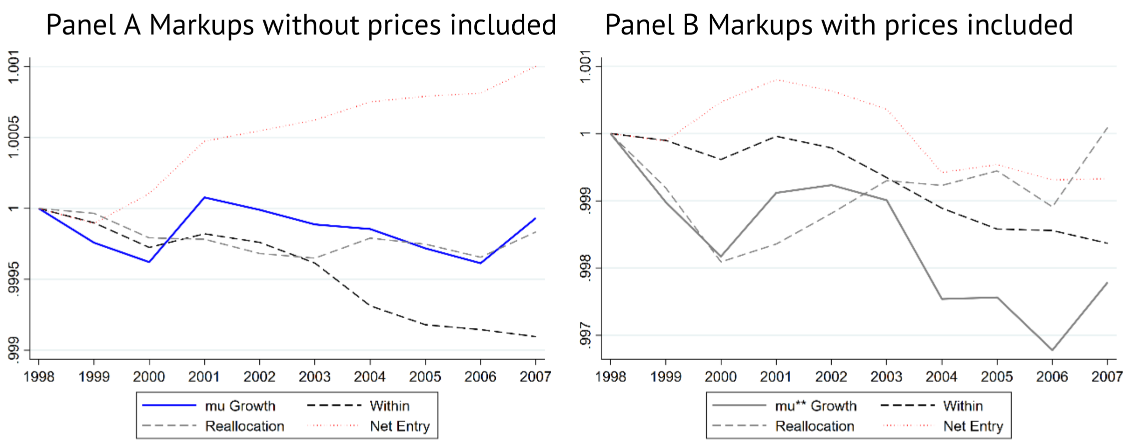

Figure 7. Cumulative Revenue-based Markups Growth

Notes: The figure plots the cumulative dynamic growth patterns of TFP measures from 1998 to 2007, with (Panel B, μ^{**}) and without (Panel A, μ) input and output price corrections. The aggregate growth is set to 1 in 1998.

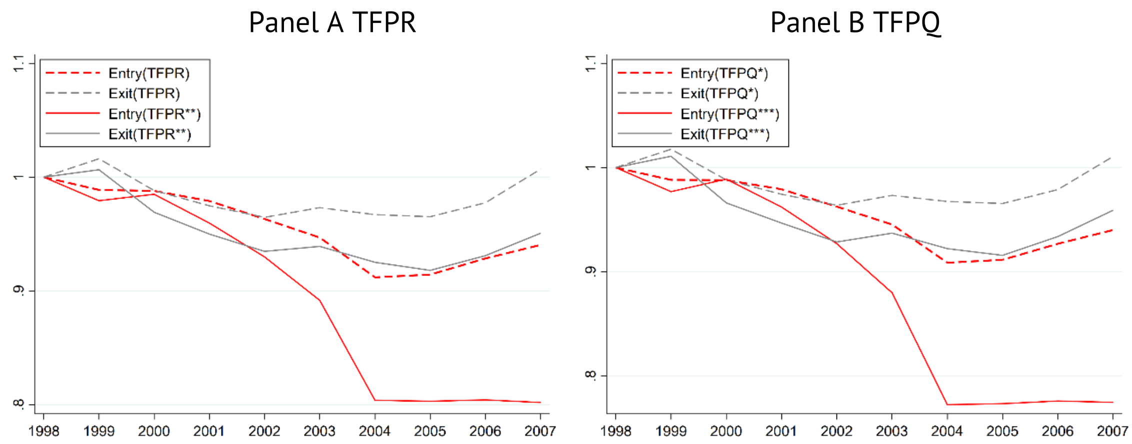

Figure 8. TFP - Firm Entry and Exit through Price Corrections

Notes: The figure plots the cumulative dynamic growth pattern of net entry through TFPQ* ($(\lambda+\omega)^{*}$ without price corrections), TFPQ*** ($(\lambda+\omega)^{***}$ with price corrections), TFPR (Ψ without price corrections), TFPR** (Ψ^{**} with price corrections), μ (without price corrections) and μ^{**}(with price corrections) through 1998-2007.

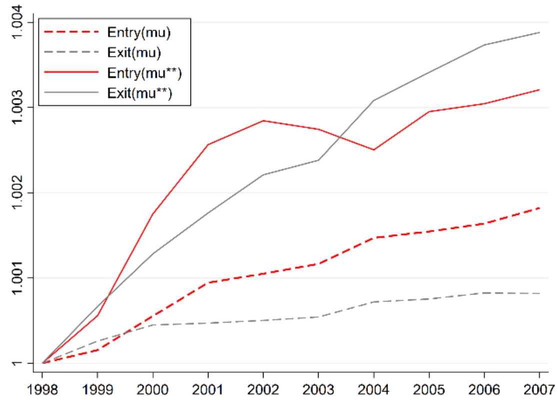

Figure 9. Markups - Firm Entry and Exit through Price Corrections

Notes: The figure plots the cumulative dynamic growth pattern of net entry through TFPQ* ($(\lambda+\omega)^{*}$ without price corrections), TFPQ*** ($(\lambda+\omega)^{***}$ with price corrections), TFPR (Ψ without price corrections), TFPR** (Ψ^{**} with price corrections), μ (without price corrections) and μ^{**}(with price corrections) through 1998-2007.

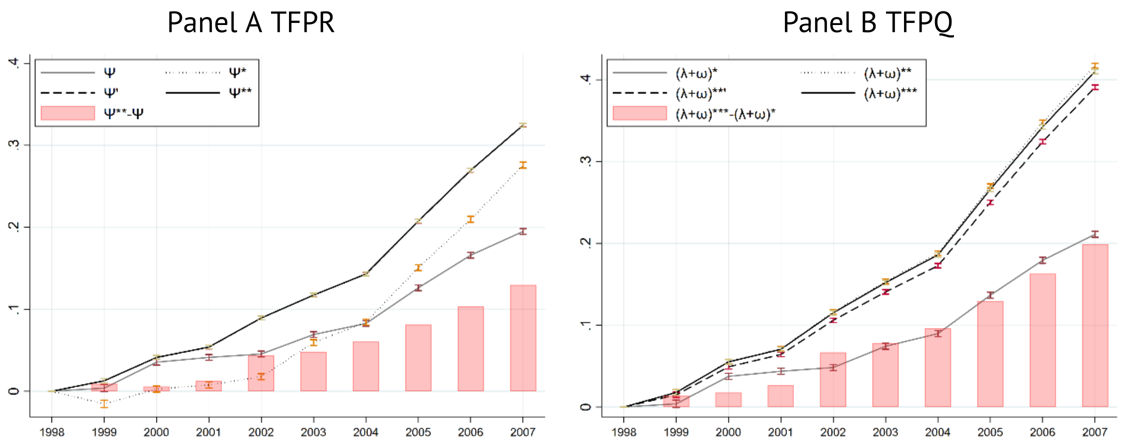

Figure 10 Aggregate TFP on Quality Level

Notes: The figure plots estimates based on $\ln X'_{ijt} = \alpha + \gamma_t + \delta_j + \varepsilon_{ijt}$ with 95% confidence intervals (vertical bars) included based on clustering at the firm level. The left panel shows estimates of TFPR (Ψ without prices correction, Ψ^* with output prices correction, $\Psi^{*'}$ with input prices correction, and Ψ^{**} with input and output prices correction), and the right panel shows estimates of TFPQ* ($(\lambda+\omega)^*$ without prices correction, $(\lambda+\omega)^{**}$ with output prices correction, $(\lambda+\omega)^{**'}$ with input prices correction, and $(\lambda+\omega)^{***}$ with input and output prices correction). The terms $\Psi^{**} - \Psi$ and $(\lambda+\omega)^{***} - (\lambda+\omega)^*$ represent the differences between the estimates. All estimates are normalised to the year 1998, which is set as the baseline (zero).

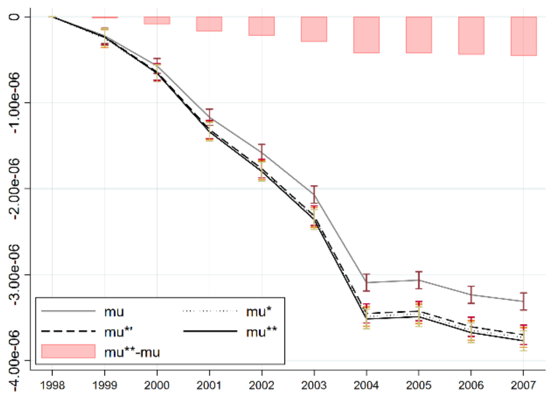

Figure 11. Aggregate Markups on Quality Level

Notes: The figure plots estimates based on $\ln X'_{ijt} = \alpha + \gamma_t + \delta_j + \varepsilon_{ijt}$ with 95% confidence intervals (vertical bars) included based on clustering at the firm level. The graph shows estimates of markups (μ without prices correction, μ^* with output prices correction, $\mu^{*'}$ with input prices correction, and μ^{**} with input and output prices correction). The term $\mu^{**} - \mu$ represents the differences between the estimates. All estimates are normalised to the year 1998, which is set as the baseline (zero).

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