Comparing Productivity when Products and Inputs Differ in Quality: China Manufacturing Growth 1998-2013*

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Abstract

We measure and compare productivity when products and inputs are heterogeneous in quality, analyzing productivity growth in China manufacturing 1998-2013. Growth was mostly based on the introduction and development of new products, in particular by entrants. Not controlling for quality, measured productivity understimates productivity by the amount of the quality dimension of production, and overstimates it by the effect of the higher quality of the inputs. To control for input quality we specify the inputs of the production function in the form of standardized quantities. To identify the direct effect of quality on production and productivity we use the demand for the product (set of products) of the firm, assuming that the firm sets optimally the unobserved level of quality. Not all demand heterogeneity, however, can be assumed to be due to quality.

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1. Introduction

Everything else being equal, the level of demand for two substitute products may differ in two ways linked to differentiation. First, with the products sold at the same price each product meets specific tastes/needs of different segments of consumers. We say that the product demands differ because product characteristics associated to horizontal differentiation. Second, one product has characteristics preferred by all consumers. In this case we say that the good has higher quality and demands differ according to a pattern of vertical differentiation. It is natural to assume that the product with superior quality will be more costly to produce and its price will be higher. Some consumers will buy the inferior variety because the additional utility brought by the superior product doesn't compensate the utility sacrifice implied by the higher price. We observe market equilibria in which consumers have sorted themselves between the products, both taking into account their preferences and the marginal utility effects of their budget constraints.

Productivity in the production of products that differ in quality is hard to compare. The usual regret of many economists, that would like to have data on physical quantities of the products for productivity analyses, losses here any bite. Quantities of goods of different quality are not comparable, so we face a problem that starts with the numerator of any productivity measure. On the other hand, the inputs used in the production of goods of different quality are likely to be of different quality as well. For instance, it is standard to have quantities of labor in the form of number of workers or hours of work. However, this is not the appropriate measure if the labor employed in each production has different levels of quality (level of skills). So the problem continues with the denominator of any measure of productivity, even simple labor productivity.

The production function, the tool that is customarily used to measure the relationship between output and inputs, implicitly assumes that the products and inputs of all firms for which we compare productivity are homogeneous. This is the very foundation of productivity analysis. Productivity is taken as the (usually neutral) shift in the frontier representing maximum outputs given input quantities. This frontier is assumed the same for all firms except for its distance to the origin.[1]

Economic theory and applied analysis have developed, however, ways to integrate quality in the framework of the production function. With respect to the quality of the output, a natural way to introduce quality is to consider that the output of the production function is multidimensional (see the recent microdata example of Grieco and McDevitt, 2017). One dimension of the output is quantity and another dimensions is quality.[2] With respect to the quality of the inputs, there is an extended literature that has studied the way to measure the inputs in comparable terms taking into account their quality differences (see, for example, the initial works of Griliches, 1957, and Jorgenson and Griliches, 1967)[3]. High skilled workers, for example, can be measured in equivalent numbers of workers of standard quality. A production function in terms of normalized or standardized quantities of inputs retains in principle all properties of traditional production functions in homogeneous inputs across firms.

More formally, dropping for simplicity firm and time subindices, the production function that is relevant for the analysis of productivity of firms in a product differentiated industry with quality differences is

$$h(Y, \delta_Q) = F(X^*(X, \theta)) \exp(\omega^* + e).$$

where Y is output quantity, δ_Q is the relevant index of quality, X^* is a vector of standardized quantities of inputs which is a vectorial function of the quantities X and the vector of quality indices θ, ω^* represents productivity and e is an uncorrelated error of observation (see Jaumandreu, 2016). Solving for quantity, under some simplifying conditions we can

[1] The recent literature on estimating production functions with varying coefficients, however, relaxes this framework. See Balat, Bramvilla and Sasaki (2015); Fox, Hadal, Holderlin, Petrin and Sherman (2016), and Kasahara, Schrimpf and Suzuki (2016).

[2] We can measure quality by a quality index summarizing the relevant product attributes that make the product preferable.

[3] Recently De Loecker, Goldberg, Khandelval and Pavnik (2016) have proposed to use the output price in a control function approach to address the problem.

approximate the result by

$$Y = F(X)\exp(\omega^* - \alpha(\delta_Q) + \theta\beta + e) = F(X)\exp(\omega + e).$$

where β is a vector of input elasticities and $\alpha(\cdot)$ is a function increasing (at an increasing rate) in the index of quality. Notice that the production function $F(\cdot)$ has now observed input quantities as arguments.

In the last equality $\omega = \omega^* - \alpha(\delta_Q) + \theta\beta$. This expression tells us that, in the absence of an specification that controls for input and output quality, measured productivity ω differs from productivity ω^*. Measured productivity is lower than productivity by the amount of the quality dimension of production, and greater than productivity by the effect of the higher quality of the inputs. In general we do not know which productivity (measured or real productivity) is greater, but nothing indicates that the two effects should compensate each other.

Our analysis is motivated by the interest in measuring unbiasedly productivity ω^*. First, because it is a measure of the real productive efficiency of the firm, that can be understood previous to the decision to allocate or not part of it to the production of quality. It allows a comparison that would be meaningless in terms of productivity net of quality for firms that differ in the content of quality. Second, because it is convenient to have a measure of firm's efficiency separated to the degree of quality of inputs, in particular the skills of labor force. Separating the components of "apparent" productivity we make possible a deeper analysis of the decisions of the firms. For example, we can measure the relative amount of efficiency that firms sacrifice for quality or quality improvements. And we can get economic insights on this decision: is this relative amount correlated with the degree of productivity shown by the firm? On the other hand, we can ask how correlated are output and input quality and if input quality is a prerequisite of output quality. As we will see later, all these questions have policy implications.

In this paper we separately measure productivity ω^*, the effect of quality $\alpha(\delta)$ on productivity, and the effect of worker skills (we have not data enough to fully assess the effect of the quality of materials). To control for input quality we specify the inputs of the production function in the form of standardized quantities, what amounts to use the expenditures on each input divided by the appropriate price of a standard unit of the input. In the case of labor, for example, we use the wage bill divided by the average industry wage. As we also have the number of workers, in this case we are able to identify separately both the standardized quantity of labor and the index of quality (the average firm-level wage divided by the average industry wage).

To identify the effect of quality on production and productivity we use the demand for the product (set of products) of the firm. We assume that the quality attributes of the product are represented by the unobservable δ_Q, that makes the price at which the firm can sell a given quantity higher given the values of the observable shifters (age, location, sales effort).[4] Our identification assumption is just that quality has an effect $\alpha(\delta_Q)$ on productivity. In setting the optimal level of quality the firm equates (appropriately weighted) the marginal impact of quality in revenue and the marginal impact of quality on cost (the impact on productivity is passed on, by duality, to cost). We are working with different versions of this optimality condition (static, dynamic) and different ways to approximate the effect of it.

Our aim is to measure and compare firm-level productivities robust to quality, as well as the evolution of quality, in China manufacturing 1998-2013. During this period, China manufacturing experienced a huge growth. Firms' sales increased at a high pace both domestically and in the market for exports. This growth was based on an intense product turnover. Only a limited proportion of firms alive at the beginning of the period survives, and hence the most important part of the huge increase of sales is made of the start of economic activity (entry) and growth of new firms, which contribute and develop new products. Jaumandreu and Yin (2018) shows how demand heterogeneity of all firms, and in particular of the new firms, is as dispersed as the differences in productive efficiency. In addition, Jaumandreu and Yin (2018) shows how demand advantages and measured productivity are negatively correlated, what strongly suggests the presence of pervasive effects

[4] Notice that δ_Q is different, in fact only part, from the demand heterogeneity specified as δ in Jaumandreu and Yin (2018).

of quality. To properly compare productivity of all kind of firms (incumbents and entrants, state owned and private firms, exporters and non-exporters, firms with and without R&D activities), and to assess the strengths and weaknesses of all this growth, we dramatically need to measure separately gross productivity, quality and skills improvement.

There is a literature that has documented Chinese productivity growth and evaluated its determinants. Young (2003) used macro-level data, adjusting for some potential sources of measurement error in capital, labor, inflation, etc., and found that productivity growth of Chinese nonagricultural economy during 1978-1998 was 1.4 percent per year, a number "respectable but not outstanding". Brandt, Van Biesebroeck, and Zhang (2012) used microdata on manufacturing firms (from the same source as ours) to estimate manufacturing productivity during 1998-2007. They specified firms production as carried out by means of a gross production function. They concluded that the yearly growth rate was 2.8%, the highest compared to other contemporary growths. They also stress the "dynamic force of creative destruction," with net entry being one of the engines of productivity growth during the period. Hsieh and Klenow (2009) used the same microdata to estimate allocation efficiency in China. They find significant marginal cost differences among firms that they take as a sign of "price distortions" and hence misallocation. Jaumandreu and Yin (2018) provide a description of productivity growth which agrees with the numbers by Brandt, Van Biesebroeck and Zhang (2012). However, without denying the possibility of some misallocation, they find evidence for the alternative of product heterogeneity as the main source of cost differences.

The ultimate goal of this paper is to measure and compare firm-level productivities robust to quality, as well as the evolution of quality. In what follows, however, we develop the framework and only engage in a very preliminary exercise carried out with data 1998-2008 (we are working with the rest of data). The results are highly encouraging. Our estimates show that the main engines of growth were the new firms, growing very fast after entry, during a presumably stage of learning-by-doing, converging later to the average productivity growth. Our preliminary estimates are already robust to input quality but still not necessarily to different dimensions of product differentiation. Next steps of this research will involve more explicit controls and check of the role of vertical and horizontal differentiation.

The rest of this paper is organized as follows. In the next section, we set out a general framework with input and output quality heterogeneity and start to discuss how to estimate it. The third section sets out a preliminary model to explore the data. The forth section is dedicated to introduce the data and comment on the main facts about Chinese manufacturing during the period. Section 5 reports estimation results, describes productivity growth and comments on its sources. Section 6 concludes with some remarks. Appendix A gives definitions of the used variables.

2. A model with heterogeneous output and inputs.

Firm's demand with vertical and horizontal differentiation$u$

Consider a monopolistically competitive industry, where firm j produces a different product (set of products) than the product of its competitors. Differentiation can be vertical, horizontal or a combination of both. Let's first discuss demand for the product of the firm. Assume for the moment that there are not other determinants of heterogeneity than price and embodied product attributes (i.e. assume that product observable characteristics like age, location and sales effort are controlled). The product can be different because meets the specific tastes/needs of a different group of consumers (horizontal differentiation) or because its quality (at the same price all consumers would choose the highest quality product). We adopt a specification of the firm demand that it is a first order approximation (in logs) to any demand

$$y_{jt} = \alpha_0 - \eta_{jt}(p_{jt} - \overline{p}_{jt} - \delta_{Qjt}) + \delta_{Hjt} + u_{jt}.$$

where y_{jt} stands for the demanded quantity of the product, p_{jt} for its price and $\overline{p}_t$ represents the industry average price (we use lowercase letters to denote the logs of the variables). The elasticity of demand is assumed firm and time specific. The unobservables δ_{Hjt} and δ_{Qjt} account for differences in demand linked to horizontal and vertical differentiation of the product respectively. The error u_{jt} is observational, assumed uncorrelated with everything.

The demand for the product has an expectation independent from the unobservables when $p_{jt} - \overline{p}_t = \delta_{Qjt}$ and $\delta_{Hjt} = 0$. In this case $E(y_{jt}|p_{jt} - \overline{p}_{jt} - \delta_{Qjt}, \delta_{Hjt}) = E(y_{it}|0,0) = \alpha_0$. We observe the sales of the firms differing from this value according to two dimensions. Even with no quality advantages, $\delta_{Qjt} = 0$, a particular firm j can sell more (less) than a standard firm at the average price $\overline{p}_t$ because its relative product horizontal differentiation advantage embodied in δ_{Hjt}. On the other hand, even if $\delta_{Hjt} = 0$, firm j can still sell the same quantity than the average while setting a higher price than the average as long as the relative advantage embodied in δ_{Qjt} is such that $p_{jt} - \overline{p}_t = \delta_{Qjt}$. Notice that this defines implicitly the content of the index of quality: amount in percentage that the firm can raise its price above mean price due to quality without affecting its demand.

Assume now for completeness that there is a vector of z_{jt} observed characteristics with an effect $z_{jt}\alpha$, where α is a vector of parameters. Also, abusing notation call p_{jt} to the relative price $p_{jt} - \overline{p}_{jt}$. Adding p_{jt} to each side of our basic demand relationship we have

$$r_{jt} = \alpha_0 - (\eta_{jt} - 1)p_{jt} + z_{jt}\alpha + \eta_{jt}\delta_{Qjt} + \delta_{Hjt} + u_{jt}, \tag{1}$$

where r_{jt} represents log of revenue.[5]

Production function with output and input quality differences

Firm i produces the output quantity y_{jt} using capital, labor and materials. Capital is given and labor and materials are freely variable. There are two important peculiarities to take into account in the specification of this production function. First, outputs differ in quality. We take this into account assuming that the inputs of the firm can ensure different combinations of quantity and quality reflected by a transformation function $h(\cdot)$. Hence the multidimensional output of this production function is $h(y_{jt}, \delta_{Qjt})$.

Second, to get the same quantity of outputs of different quality firms may use either different quantities of the same inputs or similar quantities of inputs of different quality.

[5] Altenatively, inverting the equation for price, adding y_{jt} to each side to have a relationship in terms of revenue we have

$$r_{jt} = \frac{\alpha_0}{\eta_{jt}} + (1 - \frac{1}{\eta_{jt}})y_{jt} + \frac{z_{jt}\alpha}{\eta_{jt}} + \delta_{Qjt} + \frac{\delta_{Hjt}}{\eta_{jt}}.$$

We assume that input markets are competitive and we measure the inputs in standardized quantities by dividing the expenditure on the input by an index of the price of a unit of standard input (see Jaumandreu, 2016). In this context, expenditure divided by the unit price equals quantity of the input times an index of quality, and this product is what we call standardized quantity. Let's use asterisk for the standardized quantities. The production function can be written as

$$h(y_{jit}, \delta_{Qjt}) = F(K^*_{jt}, L^*_{jt}, M^*_{jt}) \exp(\omega^*_{jt} + e_{jt}).$$

where e_{it} is an uncorrelated error.

Assuming for simplicity $h(y_{jt}, \delta_{Qjt}) = y_{jt} \exp(\alpha(\delta_{Qjt}))$ and that the production function is Cobb-Douglas (a Cobb-Douglas production function can be considered a first order approximation in logs to any production function), taking logs we have

$$y_{jt} = \beta_0 + \beta_K k^*_{jt} + \beta_L l^*_{jt} + \beta_M m^*_{jt} + \omega^*_{jt} - \alpha(\delta_{Qjt}) + e_{jt}. \tag{2}$$

Combining the demand and production function

Equations (1) and (2) represent the relevant system of demand and production function when output and inputs are heterogeneous. We have three unobservables with very specific meanings. Gross productivity ω^*_{jt} is productivity without subtracting the part that is being to be evaporated in producing higher quality. Until now, most of the work on productivity has been devoted to measure $\omega^*_{jt} - \alpha(\delta_{Qjt})$ or productivity net of quality, that is a relevant measure but doesn't inform about the potential of productivity of the firm and it is non strictly comparable across firms with products that differ in quality.

But heterogeneity cannot be assumed coming exclusively from vertical differentiation. There is heterogeneity that comes from the purely horizontal differences in demand, represented by δ_{Hjt}. Importantly, we expect δ_{Qjt} to enter in the determination of net productivity in (2) but we can safely assume that this not the case for δ_{Hjt}.

Without observing output prices, in practice a frequent situation, we cannot try to estimate independently equation (2) and we have to combine equations (1) and (2). Consider the marginal cost associated to the production by means of (2) and split its log as

$mc_{jt} = \overline{mc}_{jt} - \omega^*_{jt} + \alpha(\delta_{Qjt})$, where $\overline{mc}_{jt}$ is the part that can be written in terms of observables. Considering optimal pricing $p_{jt} = \ln \frac{\eta_{jt}}{\eta_{jt}-1} + \overline{mc}_{jt} - \omega^*_{jt} + \alpha(\delta_{Qjt})$, we can replace p_{jt} in equation (1) and have[6]

$$\begin{aligned} r_{jt} &= \alpha_0 - (\eta_{jt}-1)\ln\frac{\eta_{jt}}{\eta_{jt}-1} - (\eta_{jt}-1)\overline{mc}_{jt} + z_{jt}\alpha \\ &\quad +(\eta_{jt}-1)\omega^*_{jt} - (\eta_{jt}-1)\alpha(\delta_{Qjt}) + \eta_{jt}\delta_{Qjt} + \delta_{Hjt} + u_{jt}. \end{aligned} \tag{3}$$

This equation, or its alternative in footnote, makes clear several problems of the standard estimates of productivity carried out with an (industry deflated) revenue dependent variable. Under output and input heterogeneity, even assuming the inputs properly measured in standarized quantities, measured productivity is the composite $(\eta_{jt}-1)\omega^*_{jt} - (\eta_{jt}-1)\alpha(\delta_{Qjt}) + \eta_{jt}\delta_{Qjt} + \delta_{Hjt}$, a mix of productivity, quality effects and horizontal heterogeneity of sales weighted by the elasticity of demand[7]

Elasticity of demand

Many papers approach equations like (3) or its alternative in footnote using strong restrictions on the elasticity of demand. We think that it is important to be more general. Here we are going to use a method due to Jaumandreu and Yin (2018) that only needs to assume static pricing. A robust estimate of the elasticity of demand, not separable from the short-run elasticity of scale of the firm, can be obtained using a regression based on the following chain of relationships

$$\begin{aligned} \frac{R_{jt}}{VC_{jt}} &= \frac{P_{jt}Y_{jt}}{VC_{jt}} = \frac{P_{jt}}{\frac{VC_{jt}}{Y^*_{jt}}\frac{Y^*_{jt}}{Y_{jt}}} = \frac{P_{jt}}{AVC_{jt}}\exp(e_{jt}) = \frac{P_{jt}}{\nu MC_{jt}}\exp(e_{jt}) \\ &= \frac{1}{\nu}\frac{\eta_{jt}}{\eta_{jt}-1}\exp(e_{jt}) = a(S_{jt})\exp(e_{jt}), \end{aligned}$$

where Y^*_{jt} is output chosen at the moment that the inputs are decided, the fourth equality

[6] Substituting (2) for y_{jt} in the demand function

$$\begin{aligned} r_{it} &= \frac{\alpha_0}{\eta_{it}} + (1-\frac{1}{\eta_{it}})\beta_0 + (1-\frac{1}{\eta_{it}})(\beta_K k^* + \beta_L l^* + \beta_M m^*) + z_{it}\frac{\alpha}{\eta_{it}} \\ &\quad +(1-\frac{1}{\eta_{it}})\omega^*_{it} - (1-\frac{1}{\eta_{it}})\alpha(\delta_{Qit}) + \delta_{Qit} + \frac{\delta_{Hit}}{\eta_{it}} + v_{it}\ . \end{aligned}$$

where $v_{it} = (1-\frac{1}{\eta_{it}})e_{it}$.

[7] In the alternative specification, productivity is $(1-\frac{1}{\eta_{it}})\omega_{it} - (1-\frac{1}{\eta_{it}})\alpha(\delta_{Qit}) + \delta_{Qit} + \delta_{Hit}/\eta_{it}$.

comes from the relationship that links average and marginal costs according to the short-run elasticity of scale $\nu = \beta_L + \beta_M$, the fifth uses the static pricing assumption, and the sixth expresses $\frac{1}{\nu}\frac{\eta_{jt}}{\eta_{jt}-1}$ as a function to be estimated of a vector of observables S_{jt}. From the latest equality, the elasticity of demand can be expressed as

$$\eta_{it} = \frac{a(S_{it})\nu}{a(S_{it})\nu - 1}.$$

Equation (3) may be seen as part of a system with a first equation specifying the markup. The system may be estimated simultaneously or the result of the first equation can be imposed in the form of restriction in the second equation.

Discussion

Equation (3) (or its alternative in footnote) is the type of equation that one obtains when there are not firm-level output prices available. With two differences. The first is that inputs are measured in standardized quantities. The second is that the composite of productivity and demand heterogeneity, which papers without prices obtain, is further decomposed in the results of heterogeneity due to horizontal and vertical or quality differentiation (see Guillard, Jaumandreu and Olivari, 2018, for a comparison). It shares with previous estimates the convenience of adding an equation of the margin to help the identification of the elasticity of demand. It goes beyond Jaumandreu and Yin (2018) in that the heterogeneity of demand is decomposed in two types, and hence the two market (two revenue equations) identification strategy of this paper is not enough. How we can identify $\omega^*_{jt}, \delta_{Qjt}$ and δ_{Hjt}?

Paradoxically, it is the complication of the two types of demand heterogeneity what can help to solve the problem of identification. Under sensible assumptions, the endogenoeus choice of quality on the part of the firm gives us a new equation that can be used to write the quality unobservable in terms of observables. Let's first assume that the choice of quality can be carried out in a perfectly flexible way each period. That is, the firm chooses δ_{Qjt} simultaneously to P_{jt} (and the inputs to carry out production). As we want to show that the solution is very general, let's set the problem without using specific functional forms. The firm maximizes each period

$$\pi_{jt} = P_{jt}Y_{jt}\left(\frac{P_{jt}}{\exp(\delta_{Qjt})}, \delta_{Hjt}\right) - VC(W_{jt}, Y_{jt}\left(\frac{P_{jt}}{\exp(\delta_{Qjt})}, \delta_{Hjt}\right), \delta_{jt}),$$

where W_{jt} is the vector of prices of variable inputs and $Y_{jt}\left(\frac{P_{jt}}{\exp(\delta_{Qjt})}, \delta_{Hjt}\right)$ is demand. Notice that we adopt the same definition of quality heterogeneity as before, imposing it to have the same semielasticity than the elasticity of demand.

The FOC with respect to price of this equation gives the usual price-cost margin equation

$$P_{jt} - MC_{jt} = -\frac{Y_{jt}}{\frac{\partial Y_{jt}}{\partial P_{jt}}}.$$

The FOC with respect $\delta_{Q_{jt}}$ is

$$\frac{\partial \pi_{jt}}{\partial \delta_{Qjt}} = -P_{jt}\frac{P_{jt}}{\exp(\delta_{jt})}\frac{\partial Y_{jt}}{\partial \exp(\delta_{Qjt})} + MC_{jt}\frac{P_{jt}}{\exp(\delta_{jt})}\frac{\partial Y_{jt}}{\partial \exp(\delta_{Qjt})} - \frac{\partial VC_{jt}}{\partial W_{jt}}\frac{\partial W_{jt}}{\partial \delta_{Qjt}} - \frac{\partial VC_{jt}}{\partial \delta_{Qjt}} = 0.$$

Noticing that $\frac{P_{jt}}{\exp(\delta_{jt})}\frac{\partial Y_{jt}}{\partial \exp(\delta_{Qjt})} = P_{jt}\frac{\partial Y_{jt}}{\partial P_{jt}}$, assuming for simplicity L_{jt} as the only input that is price sensitive to the choice of quality say, and applying Shephard Lemma, we can write

$$\frac{1}{W_{jt}}\frac{\partial W_{jt}}{\partial \delta_{Qjt}}S_{Ljt} + \frac{1}{VC}\frac{\partial VC_{jt}}{\partial \delta_{jt}} = -\frac{1}{VC_{jt}}(P_{jt} - MC_{jt})P_{jt}\frac{\partial Y_{jt}}{\partial P_{jt}}$$

or

$$\varepsilon\nu S_{Ljt} + \alpha'(\delta_{Qjt}) = \frac{\eta_{jt}}{\eta_{jt} - 1}, \tag{4}$$

where $\varepsilon = \frac{1}{W_{jt}}\frac{\partial W_{jt}}{\partial \delta_{Qjt}}$ is assumed to be a parameter, $S_{Ljt} = \frac{W_{jt}L_{jt}}{VC_{jt}}$, and $\alpha'(\delta_{Qjt})$ stands for the derivative $\frac{\partial \alpha(\delta_{Qjt})}{\partial \delta_{Qjt}}$. Equation (4) is saying that the optimal choice of quality should equate the marginal (percentage) benefit of having more quality (the markup $\frac{\eta_{jt}}{\eta_{jt}-1}$) with the two (percentage) increases in costs due to improved quality: the cost incurred through higher wages to be paid to more skilled workers (a term in better materials could be added) and the cost of sacrificed productivity.

Unobserved equilibrium quality will satisfy the equation

$$\alpha'(\delta_{Qjt}) = \frac{\eta_{jt}}{\eta_{jt} - 1} - \varepsilon\nu S_{Ljt},$$

and taking into account that $\alpha'(\cdot)$ is an invertible function of δ, we can write δ_{Qjt} as an unknown function $\varphi(\cdot)$ of the observables markup and labor share

$$\delta_{Qjt} = \varphi(\frac{\eta_{jt}}{\eta_{jt} - 1} - \varepsilon\nu S_{Ljt}). \tag{5}$$

This suggests a way to identify to identify $-(\eta_{jt}-1)\alpha(\delta_{Qjt})+\eta_{jt}\delta_{Qjt}$ in equation (3): replace δ_{Qjt} by the polynomial in observables (5).

A subtlety that it is worthy of noticing. Consider the Taylor equation $\alpha(0) = \alpha(\delta_{Qjt}) - \frac{\partial\alpha(\delta_{Qjit})}{\partial\delta_{Qjt}}\delta_{Qjt} - \frac{\partial^2\alpha(\delta_{Qjt})}{\partial\delta_{Qjt}^2} - ....$ It implies, if we assume $\alpha(0) = 0$, that $\alpha(\delta_{Qjt}) = \frac{\eta_{jt}}{\eta_{jt}-1}\delta_{Qjt} + \frac{1}{2}\alpha''(\delta_{Qjt})\delta_{Qjt}^2 + ...$, so $-(\eta_{jt}-1)\alpha(\delta_{Qjt}) + \eta_{jt}\delta_{Qjt} = \frac{1}{2}\alpha''(\delta_{Qjt})\delta_{Qjt}^2 + ...$ This suggests that, if function $\alpha(\cdot)$ is linear, the need to control for heterogeneity in the revenue function may disappear completely (a point that was suggested by Katayama, Lu and Tybout, 2009). But, if this is not the case, only terms of order 2 and higher are needed in controlling for vertical differentiation.

In equation (3) we additionally need to control for the demand heterogeneity created by the horizontal effects δ_{Hjt}. The most simple way to do this seems though fixed effects, been confident that the heterogeneity by this motive is relatively stable over time. So, a realistic plan for assessing equation (3) would be to run it (after having an estimate of $a(S_{it})$) specifying fixed effects and including high order terms of a polynomial in $\frac{\eta_{jt}}{\eta_{jt}-1} - \varepsilon_L S_{Ljt} - \varepsilon_M S_{Mjt}$. This can be used to test if observed costs are sensitive to quality of labor and materials, as well as to the unobservable cost effects of quality, at the same time that it is tested if the effects of quality on productivity are linear. If the effects are linear, equation (3) without any quality control would produce the right estimate of ω^*.

This discussion should be completed with the strategy to follow if quality, as it is likely, cannot be considered to be adjusted without frictions over time. In this case the valid first order condition comes from a dynamic specification.

3. A simple exploratory model

Estimation equations

Lets momentarily assume: 1) Vertical differentiation effects cancel (the function $\alpha(\cdot)$ is linear) and horizontal effects are iid after using demand shifters; 2) The elasticity of demand only changes across firms; 3) The process for ω_{jt}^* is $\omega_{jt}^* = \beta_t + g(\omega_{jt-1}^*) + \xi_{jt}$; 4) The effect of sales effort, a_{jt}, is picked up by the unknown function $h(a_{jt})$. Under these assumptions, the alternative in footnote to equation (3) becomes

$$r_{jt} = \frac{\alpha_0}{\eta_j} + (1 - \frac{1}{\eta_j})\beta_0 + (1 - \frac{1}{\eta_j})\beta_t + (1 - \frac{1}{\eta_j})(\beta_K k_{jt}^* + \beta_L l_{jt}^* + \beta_M m_{jt}^*) + \frac{h(a_{jt})}{\eta_j} + z_{jt}\frac{\alpha}{\eta_j} + (1 - \frac{1}{\eta j})g(\omega_{jt-1}^*) + \zeta_{jt}, \tag{6}$$

where $\zeta_{it} = (1 - \frac{1}{\eta_j})(e_{jt} + \xi_{jt})$ and z_{jt} represents the shifters different from sales effort. The inversion of the first order condition for materials gives

$$\omega_{jt-1}^* = -\frac{\eta_j}{\eta_j - 1}\ln\beta_M - \frac{\alpha_0}{\eta_j} + \frac{\beta_0}{\eta_j - 1} + (p_{Mt-1} + m_{jt-1}^*) - (\beta_K k_{jt-1}^* + \beta_L l_{jt-1}^* + \beta_M m_{jt-1}^*) - \frac{h(a_{jt-1})}{\eta_j} - z_{jt-1}\frac{\alpha}{\eta_j} - \frac{\eta_j}{\eta_j - 1}\ln(1 - \tau_{jt-1}) \ . \tag{7}$$

where τ_{jt-1} stands for sales-related taxes. We estimate equation (6) with ω_{it-1} replaced by expression (7).

Sales effort a_{jt} is the ratio of sales expenditure to total production cost. In the vector z_{jt} we include the location dummies (eastern area, middle area, firm belonging to the economic center, city that is a province capital) and the export dummy (see Jaumandreu and Yin, 2018, for the construction of variables and Appendix A for a short definition on the variables included in this exercise).

Elasticity

From the first order condition of L_{jt} and M_{jt} in short-run cost minimization we have

$$\frac{R_{jt}}{P_{Mt}M_{jt}^* + W_t L_{it}^*} = \frac{P_{jt}}{MC_{jt}}\frac{1}{(\beta_L + \beta_M)}\exp(e_{jt}) \, .$$

Noticing that $\frac{P_{jt}}{MC_{jt}} = \frac{1}{1-\tau_{jt}}\frac{\eta_j}{\eta_j - 1}$, taking logs and averaging over time (assuming $\sum\limits_t e_{jt} = 0$ for each j) gives

$$\ln(\frac{\eta_j}{\eta_j - 1}) = \frac{1}{N_j}\sum_t \ln\left(\frac{(1-\tau_{jt})\, R_{jt}}{P_{Mt}M_{jt}^* + w_t L_{jt}^*}\right) + \ln(\beta_L + \beta_M) \, ,$$

where $\frac{1}{N_j}\sum_t \ln\left(\frac{(1-\tau_{jt})R_{jt}}{P_{Mt}M_{jt}^* + w_t L_{jt}^*}\right)$ is firm j's average log share of net revenue over variable cost. Therefore, we can express demand elasticity η_j as a function of an observable and the short-run output elasticity of variable inputs, i.e.

$$\eta_i = \frac{\exp\left[\frac{1}{N_j}\sum_t \ln\left(\frac{(1-\tau_{jt})R_{jt}}{P_{Mt}M^*_{jt}+w_t L^*_{jt}}\right) + \ln\left(\beta_L+\beta_M\right)\right]}{\exp\left[\frac{1}{N_j}\sum_t \ln\left(\frac{(1-\tau_{jt})R_{jt}}{P_{Mt}M^*_{jt}+w_t L^*_{jt}}\right) + \ln\left(\beta_L+\beta_M\right)\right]-1}.$$

We can substitute this expression for the elasticity of demand in the equation formed from (6) and (7).[8]

Moments

The residual of equation (6) is a function of parameters θ to be estimated. We base our estimation on the moment restrictions

$$E\left[A(z_i)\cdot\zeta_i(\theta)\right] = 0,$$

where $A(z_j)$ is a matrix $L \times T_j$ of functions of the exogenous variables z_j, $\zeta_j(\theta)$ is a vector $T_j \times 1$ and L is the number of moments. The GMM problem is

$$\underset{\theta}{Min}\left[\frac{1}{N}\sum_j A(z_j)\zeta_j\left(\theta\right)\right]' W_N \left[\frac{1}{N}\sum_j A(z_j)\zeta_j\left(\theta\right)\right],$$

where N is the number of firms. We use the two-step GMM estimator of Hansen (1982). We first obtain a consistent estimate $\widehat{\theta}$ of θ with a weighting matrix $W_N = \left(\frac{1}{N}\sum_j A(z_j)A(z_j)'\right)^{-1}$. In the second step we then compute the optimal estimate with weighting matrix $W_N = \left(\frac{1}{N}\sum_j A(z_j)\zeta_j\left(\widehat{\theta}\right)\zeta_j\left(\widehat{\theta}\right)' A(z_j)'\right)^{-1}$.

Our baseline specification has 26 parameters: three constants (two interacted with functions of the elasticity and another inside the $g(\cdot)$ function), 9 coefficients of time dummies, 4 coefficients of location dummies, export dummy, 3 production function coefficients, 3 coefficients in the series approximation of the unknown function $h\left(\cdot\right)$ and 3 coefficients more in the series approximation of the unknown function $g\left(\cdot\right)$. We search non linearly for the 3

[8] Output prices should be greater than marginal cost, i.e. $\ln(\frac{\eta_i}{\eta_i-1})$ should be set as $\max\left\{0, \frac{1}{N_i}\sum_t \ln\left(\frac{(1-\tau_{it})R_{it}}{P_{Mt}M^*_{it}+w_t L^*_{it}}\right) + \ln\left(\beta_L+\beta_M\right)\right\}$. But this function is non smooth and makes the search for parameters very difficult. Therefore, we use a continuous approximation while searching for the parameters

$$\ln(\frac{\eta_i}{\eta_i-1}) = \left[\frac{1}{N_i}\sum_t \ln\left(\frac{(1-\tau_{it})R_{it}}{P_{Mt}M^*_{it}+w_t L^{*+}_{it}}\right)\right]\cdot\frac{\exp(\beta_L+\beta_M)-1}{e\ -1}.$$

production function coefficients and the 8 parameters of the demand shifters (3 coefficients in the series approximation of $h(\cdot)$, east, middle, core, capital and export), concentrating out the rest of the parameters.

In our empirical application we use polynomials of the exogenous variables as instruments. This strategy is widely employed in the literature (see Doraszelski & Jaumandreu, 2013, or Wooldridge, 2009, version of OP/LP/ACF; i.e. Olley and Pakes, 1996, Levisohn and Petrin, 2003, and Ackerberg, caves and Frazer, 2015). We take as exogenous variables the constant, the time dummies, k_{it-1},l_{it-1}, m_{it-1} and a_{it-1}.[9] We use a basic set of 37 instruments: the constant, the time dummies (9 instruments), the location export dummies lagged (5 instruments); a univariate polynomial of degree three in a_{it-1} (3 instruments); a complete polynomial in variables k_{it-1},l_{it-1} and m_{it-1} (19 instruments). Once the model is estimated, we recover ω_{it} according to (7).

4. Data

This section freely overlaps with the data section of Jaumandreu and Yin (2018) and the details given in the online appendix of the same paper. In the current estimation we use data for the period 1998-2008, the same that in Jaumandreu and Yin (2018), but we are working on the addition of the data 2009-2013. Appendix A gives a brief detail on the definition of the variables used here.

The source of our data is the Annual Census of Industrial Production, a firm-level survey conducted by the National Bureau of Statistics (NBS) of China. This annual census includes all industrial non-state firms with more than 5 million RMB (about $600,000) in annual sales plus all industrial state-owned firms (SOEs). Our source is then the same used in Brandt, Van Biesebroeck, and Zhang (2012).[10]

Our sample consists basically of large firms and some smaller SOEs. The available information includes firm demographics such as location, industry code, the date of birth and some detail on ownership. We obtain from the data the revenue of the firm, physical

[9] In practice we will prefer not to treat k_{it} as exogenous because of presumably errors in its measurment.

[10] The same data source has been used, for example, in Hsieh and Klenow (2009).

capital, wage bill, cost of materials, the number of workers and the amount spent in sales promotion.

We want to use the data as a panel of firms, that is, we want to exploit all the observations repeated over time which are available for the same individual. One reason is that our modeling implies productivity evolving over time, whose estimation depends on the sequence of observations of the firm. Another is that we are interested in detecting the new born firms and the firms that eventually shut down. In order to make all this possible we have had to address two important and related questions: the problem of discontinuity of information and the detection of the "economic" entry and exit of firms in the middle of all the additions to and drops from the sample.

Discontinuity of information for an existing firm can happen in the raw data base for two reasons. First, if a firm is non-state owned and falls below the sales threshold of RMB 5 million. If the firm re-enters the sample keeping its ID, we only get some missing observations in the time sequence of the firm. But, when the firm doesn't re-enter sample, we unfortunately have strictly no way to distinguish its disappearance from economic shutdown. Second, and more importantly, a firm can have been allocated a different ID (9 digit-code) during the period. Firms occasionally receive a new ID if they are subject to some restructuring (change of name, ownership...), merger or acquisition. This creates a lot of broken sequences and spurious entry and exit.

We have done an intensive work (in the style of Brandt, Van Biesebroeck, and Zhang, 2012) to link over time the data of the firms that presumably had the ID changed. This process has used extensively information such the firm's name, corporate representative, 6-digit district code, post code, address, telephone number, industry code, year of birth, and has been implemented in several steps: first checking on neighbor years two by two, then longer panel sequences with the following/previous years.

The results of treating the sample in this way seem very satisfactory. Focusing on manufacturing, and considering firm time sequences with a minimum of two years, we have a total of 445,397 firms and 2,253,383 firm-year data points with information. So, after our linking, firms stay in the sample by an average of 5 years. We have time sequences of 5 or more years for more than half of the firms and more than 80% of these sequences have no interleaved missing. The degree of response of the sample firms, considered year to year, tends to be higher than 95%.

The linked data details are summarized in Table 1. Column (1) shows that the single observations discarded after the process are a small percentage, except for the starting and final years, at which the process of linking is more difficult. Columns (2) and (3) document the growth of the sample over time, particularly important in the Census year of 2004. Entry and exit, reported in columns (4) and (5), show very sensible values and explain part of this increase. Entry is defined as the set of firms newly included in the sample and born the same year or any of the two previous years. Its average rate is about 8%. The increase in newly born firms in the Census years of 2004 and 2008 is particularly high, reflecting probably the effort of administrative authorities in being exhaustive. Exit is defined as the set of firms last seen in the sample the previous year. It is hence something indirectly induced by our linking and that can include failures in the linking process as well as mixing some firms in a process of drastic downsizing. But its rate is very sensible, close to the rate of entry, somewhat decreasing over time. This seems a particular good outcome which validates the process. The resulting net entry rate (entry minus exit), reported in column (6), reversed the sign from negative to positive in 2003. Column (7) documents the increases in the sample which are not related to entry and exit. The data seem to denote a quite continuous statistical improvement of the Annual Census too, tending to include more and more firms. Part of this improvement can be related to the increase of the number of firms with a size above the threshold.

We clean the linked data according to the conditions reflected in Table 2. We set to missing value the observation of a year if there are some particularly small values in labor (less than 8 workers); some abnormal values in other variables (details in the table); or some consistency problems (details in the table). In addition, we drop 0.5% from top and bottom of the ranked variables Sales effort/Cost of principal business and Variable cost/Revenue). This enlarges the number of data points without information. We then use for each firm the time subsequence (adjacent years) of maximum length provided that is greater than one year.

Table 3 provides basic statistical information on the cleaned data. Columns (2) to (4) report unweighted averages of the firm's levels of revenue, capital and employment, and columns (5) to (7) unweighted averages of their rates of growth. Columns (2) to (4) show that revenue per firm triplicates over the period, while real capital stays at the same level and there is a significant fall in the average number of workers (more than 25%). Columns (5) to (7) show a intense average growth of output, closely followed by capital, and a positive growth for employment after 2002. In column (8) we compute a standard measure of TFP, the growth of deflated revenue minus the weighted growth of capital, labor and materials. We use as weights the average of the cost shares in moment t and $t-1$, after computing total cost as the sum of the wage bill, the cost of materials and a cost of capital calculated using a common user cost. TFP growth is strong, especially after 2001, and averages 2.9%. This matches Brandt, Van Biesebroeck, and Zhang (2012) estimates.

It is worthy to dedicate some space to comment on what this data shows about the evolution of the Chinese manufacturing during the 2000s. There is implicit in this data an spectacular growth of the industrial output accompanied by a huge growth and reallocation of productive resources. The number of firms is roughly multiplied by a factor of three. This means that, to obtain the growth of the industrial aggregates corresponding to revenue, capital and employment from the reported firm-level, we should multiply one plus the rate of growth of the corresponding mean level by three. This gives the following rough picture: nominal revenue was multiplied during the period by nine, capital by three and employment by two. The increase in output is hence based in an intense increase of productivity of the firms, on the one hand, as the calculation of TFP already made clear. Capital and labor hugely increased as well, but with an important displacement of the leading economic role to firms of smaller size. This is the reason why, despite the increase of the aggregates, capital per firm stays stable and employment per firm diminishes more than one quarter.

We split manufacturing in ten sectors which group the two-digit industries (see Table 4 for the correspondence). Table 5 provides descriptive statistics of the sample on which we are going to base our estimations. It starts by reporting the number of firms, column

(1), and observations, column (2), in each industry. Column (3) reports TFP growth in these industries to show that the main characteristics commented for the whole industry are generalized across sectors. Columns (4) to (7) report unweighted averages of revenue, capital, quality-adjusted workers and materials. We can see that firms in electronics, metals and transport equipment have larger average scale, and that firms in timber, non-metal and food are among the smallest. It clearly shows that metals, chemical and paper are capital-intensive industries, and textile, timber and machinery lie in the opposite end. Columns (8) and (9) report the degree of sales effort and variable cost share in revenue. Sales effort ranges from 3.4% to 6.8% and variable cost share from 82.5% to 88.1%. Column (10) reports the proportion of firms which export. There are remarkable differences in the proportions of firms that export, ranging from 8.2% (paper) to 42.9% (textile).

5. Results

In this section we report our preliminary results. First, we report the results of parameter estimation and characterize the distribution of ω_{jt}^{*}. Second, we decompose aggregate productivity growth by means of the OP dynamic decomposition proposed by Melitz and Polanec (2012). Third, we pay specific attention to the relationship between firm age and productivity. Finally, we make an overall assessment.

5.1. Parameter estimates and facts of productivity growth

Table 6 presents the parameter estimates of the production function and productivity process, and Table 7 of the demand shifters. Estimation is carried out by nonlinear GMM. The reported coefficients and standard errors are second stage estimates.

Columns (1) to (3) of Table 6 show the point estimates of the production function parameters. The results look globally sensible, with plausible values and low standard errors. In all 10 industries, the short-run and long-run returns to scale, $\beta_L + \beta_M$ and $\beta_K + \beta_L + \beta_M$ respectively, are reasonable. Columns (4)–(6) report the coefficients of the Markov process, approximated by an univariate polynomial of order three.

The effect of *Sales effort* is also modelled by means of a polynomial of order three. Columns (1)–(3) of Table 7 report the coefficients. The results look again sensible, with plausible values and standard errors. Columns (4) to (8) report the effects of the other shifters.

Table 8 reports some characteristics of the distribution of ω^*_{jt} and markups. We also report for comparison labor productivity. As shown in columns (1)-(2), ω and labor productivity grow very fast for all industries during 1999-2008, with the growth rate of labor productivity being systematically higher (recall that the labor input changes little on average). Figure 1 depicts the densities of the levels of ω^*_{jt} and their changes over time. The distributions turn out to be sensible and very informative, with a trend that moves to the right consistently.

Our model estimates firm-specific markups. Columns (7)–(10) of Table 8 report the distribution of the estimated markups. They are reasonable and consistent with other estimates. Columns (11)–(12) show that markups are positively correlated with ω^*_{jt} and labor productivity in all industries.

5.2. Productivity growth decomposition

We compute aggregate productivity weighting productivity levels by revenue. There are three possible channels of growth of aggregate productivity: industrial dynamics (entry and exit), improvement of allocation efficiency, and growth of the existing firms' productivity. In the first case, aggregate productivity grows if more efficient firms enter and firms of lower productivity exit. In the second case, aggregate productivity grows if market shares of the high productivity firms expand and market shares of low productivity firms shrink. In the third case, overall productivity is the result of average productivity growth of the incumbents.

To evaluate the importance of each channel we perform a decomposition of aggregate productivity in the style of Melitz and Polanec (2012). In this decomposition, entrants (exitors) contribute positively to overall productivity if they have higher (lower) productivity than incumbents. To proceed, we first decompose the revenue-weighted productivity growth of the 9 two-year periods into the contributions of three groups of firms: incumbents, entrants and exitors. Then we take the unweighted averages of the contributions. Table 9 presents these averages. It clearly shows that the spectacular productivity growth in all the 10 industries during this period is mainly based on the third channel, i.e. productivity growth of the incumbents.

In order to separately assess the effects of additions to the sample we break the firms that first show up in the sample into two groups: entry and additions to the sample. The latter happens if firms are more than 2 years old when first show up in the sample. From columns (7) and (9) we can see that the contributions of both groups are negative in all industries, which means that both entry and additions tend to be firms with lower productivity. Column (11) shows that exit has a somewhat positive contribution (except industry 8). So exitors are effectively firms of average lower productivity. The net effect of industry dynamics is however negative in all 10 industries.

Allocation efficiency improvement and industrial dynamics' contribution may be sensitive to the choice of time horizon. However, we decompose the revenue-weighted productivity growth along different time horizons and the picture remains the same.

5.3. A young-firm-populated economy

Most of Chinese manufacturing firms are rather young. Table 10 shows the median of age distribution for several years. During the period firms become even younger in all industries. In fact, after 2002 half firms are younger than 8 years in all industries.

Figure 2 shows the average productivity growth of firms during firms' life-cycle, by means of nonparametric regressions of the growth rate of productivity on firms' age. In all industries, productivity grows very fast after entry and then tends to converge to the industry average. Firms' productivity grows faster within the first 7 years in their life. Notice that, according to our results in 5.2, this rapid growth is associated with entry with lower levels of productivity than the incumbents and convergence towards average productivity.

In Table 11 we decompose survivor's productivity growth between two groups: young firms and old firms. We define young firms as those that are 8 year old or less. Table 11 shows that young firms contribute an important amount to total productivity growth in every industry, and their contribution becomes even more important in the late years of this period.

5.4. A comment

Why are there so many entrants during this period? Why is productivity growth of young firms so fast? What are the implications for our exercise?

It is a period in which the number of SOEs shrank rapidly and exports expanded greatly after China's entry into WTO in 2001. Numerous business opportunities were created owing to demand expansion domestically and overseas. A great number of private firms promptly grasped these business opportunities. Entrepreneurs knew that sales were there almost for sure and they needed not worry too much about them. These new competitors were market-oriented and reacted to market opportunities more flexibly than incumbents. They swiftly created new firms and started to produce. At the beginning their cost may be higher but they were confident that this was going to change as their experience accumulated and sales grew. It is not strange that a great number of firms entered, most with demand advantages and some cost disadvantages (see in Jaumandreu and Yin, 2018, how demand advantages are mostly contributed by entrants).

Entrants can be more efficient than incumbents because of newer technology. Meanwhile start-up costs and/or learning-by-doing may prevent entrants from immediately reaching their production frontier. Most papers find that, in fact, entrants have somewhat lower productivity than incumbents as we do. Learning-by-doing (and imitation) seems to make firms in China to mature quite quickly during this period. They reach the highest efficient level rapidly.

All these clues together give the following picture: unprecedented demand expansion during the period attracts numerous new firms to enter, that are confronted to learning-by-doing in the first years with the result that their productivity grows very fast. This implies a complex setting: most of the products are quite new, with only a few years of production, quite likely of higher quality or implying new technology, but production is also subject to a process of learning that further complicates comparisons.

6. Concluding remarks

The ultimate goal of this paper is to measure and compare firm-level productivities robust to quality. Our data are firms of China manufacturing, that was subject to a high grow of new products through an intense turnover, which implies intense evolution of quality and technology, but also needs of learning on the part of the entrants. We have used data for 1998-2008, but we are working in their enlargement up to 2013. For the moment we have employed an exploratory model, that only controls explicitly for the differences in input quality and assumes that the revenue equation produces the right estimate of productivity gross of quality (because the impact of quality on demand and productivity compensate each other and the effects of horizontal differentiation are assumed iid).

Our preliminary model produces very sensible estimates, in particular of productivity and its evolution. The results confirm the incumbents as the main source of productivity grow. But also a very important turnover with firms entering with less productivity and reaching very fast the average level. Next steps of this research should test this model against the more general formulations proposed in the first part of this paper, allowing for quality and horizontal productivity effects, using the full data set 1998-2013.

Appendix A: Variables

Age

Current year minus the year in which the firm was born.

Capital

We estimate the capital stock at birth, deflate it, and compute the real stock in the first year of observation by applying the perpetual inventory method with a series of real investments.

Capital city

Dummy that takes the value one when the firm belongs to a city that is capital of the province.

Core location

Dummy thah takes the value one when the firm belongs to the economic center. Defined as the capital city of province or their suburbs. For industry 2, 6 and 7, defined as prefecture-level (or above) city or their suburbs.

Entrant firm

For first time in the sample and born the same year or one of the two previous years.

Exitor

Firm that disappears from the sample.

Export dummy

Exports are the value of industrial export sales at current prices. The dummy takes the value one if exports are non zero.

Labor

Standardized employment computed as wage bill divided by the average wage at the 2-digit breakdown of manufaturing.

Location dummies

East or Middle, according to the location of the firm.

Materials

Standarized materials computed as cost of materials divided by the price of materials.

The price of materials is an estimate of a price index for the intermediate consumption of the industry the firm belongs to.

Revenue.

Revenue after taxes, at current prices, as reported by the firm.

Sales effort

All expenditures related to sales (e.g promotion and advertising) divided by revenue.

Wage

Average wage is obtained by dividing the wage bill by employment.

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Table 1: Manufacturing linked data[a]

Years	Discarded single obs.[b]	No. of firms[c]	Sample growth[d]	Entry rate[e]	Exit rate[f]	Net entry rate[g]	Additions[h]	Aggreg. output /Industry GDP[i]	Response rate[j]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1998	0.153	129,671	-	0.142	-	-	-	0.557	1.000
1999	0.026	145,949	0.112	0.044	-	-	-	0.578	0.971
2000	0.025	149,371	0.023	0.050	0.093	-0.043	0.066	0.608	0.955
2001	0.021	159,471	0.063	0.081	0.110	-0.029	0.092	0.605	0.950
2002	0.018	170,979	0.067	0.070	0.075	-0.005	0.072	0.638	0.946
2003	0.030	184,537	0.073	0.084	0.080	0.004	0.069	0.626	0.943
2004	0.067	247,854	0.255	0.176	0.099	0.077	0.178	0.741	0.966
2005	0.009	263,681	0.060	0.069	0.046	0.023	0.037	0.760	0.939
2006	0.010	288,433	0.086	0.088	0.055	0.033	0.053	0.813	0.953
2007	0.021	315,769	0.087	0.086	0.057	0.029	0.058	0.881	0.966
2008[k]	0.167	333,330	0.053	0.145	0.092	0.053	0.000	0.870	1.000
1998-2008		445,397							0.963

[a] We only retain firms which stay two and more years.
[b] As proportion of the remaining number of firms.
[c] There are 2,253,388 firm-year observations.
[d] New firms as proportion of number of firms at t. $Sample\ growth = Entry\ rate - Exit\ rate + Additions$.
[e] Newly included firms born in t, $t-1$ or $t-2$, as proportion of number of firms at t.
[f] Firms last seen at $t-1$ as proportion of number of firms at t. Not defined for 1998 and 1999.
[g] Entry rate - exit rate.
[h] Sample growth - net entry.
[i] $(Revenue - Cost\ of\ Materials + VA\ tax)/Industry\ GDP\ from\ China\ Statistical\ Yearbook$.
[j] Proportion of firms in sample at year t which report information.
[k] 2008 entrants, 48,369 firms, treated (in this row) as if they were to stay two or more years.

Table 2: Filters used to clean the linked data

Values are set to missing in the following cases:

Small values:
- Less than 8 workers or 30,000 RMBs in *Revenue*, *Capital*, *Wage bill*, *Cost of materials*.

Abnormal values:
- Negative value in *Exports* or *Sales effort*.
- Zero or less in finacial capital, negative value in a financial component.
- Born before 1949 or after 2008.

Consistency:
- Revenue less than *Exports*, *Sales effort* or *Variable cost* (*Wage bill*+ *Cost of materials*).
- Financial capital is less than the sum of its finacial components.

A missing value is an interruption of the firm time sequence. We only use the firm's longest time subsequence provided that is longer than one year.

Table 3: Basic descriptive statistics by year

Years	Number	Average levels			Average growth rates			TFP[d]
	of firms	Revenue[a]	Capital[b]	Labor[c]	Revenue	Capital	Labor	growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1998	67,573	47.473	31.830	376				
1999	80,717	48.466	30.322	343	0.079	-0.005	-0.004	0.024
2000	83,851	56.556	29.978	334	0.118	-0.005	0.005	0.026
2001	91,034	59.558	28.933	307	0.074	0.008	0.004	0.003
2002	99,381	65.417	27.931	294	0.132	0.031	0.022	0.030
2003	109,117	78.777	27.584	285	0.200	0.065	0.043	0.034
2004	144,603	78.004	22.808	239	0.219	0.095	0.044	0.030
2005	162,187	89.208	24.095	238	0.266	0.132	0.066	0.038
2006	183,753	100.404	24.831	229	0.238	0.104	0.045	0.012
2007	206,001	114.989	25.725	220	0.268	0.099	0.042	0.038
2008	179,179	139.032	30.283	230	0.224	0.167	0.041	0.038
1998-2008	318,543	88.943	27.019	264	0.201	0.081	0.035	0.029

[a] Nominal. Millions of RMBs.

[b] Deflated by an investment price index. Millions of RMBs.

[c] Number of workers.

[d] Growth of deflated revenue minus the growth of capital, labor and deflated materials weighted by the average cost shares between t and $t-1$ computed using a common cost of capital.

Table 4: Industry correspondence

Industry	Two-digit industries (code)
1. Food, drink and tobacco	Agricultural and By-Product Processing (13);
	Food Manufacturing (14);
	Beverage Manufacturing (15);
	Tobacco Products (16).
2. Textile,leather and shoes	Textile (17); Apparel, Shoes, and Hat Manufacturing (18);
	Leather, Fur, and Coat Products Manufacturing (19).
3. Timber and furniture	Wood Processing, and Other Wood Products (20);
	Furniture Manufacturing (21).
4. Paper and printing products	Paper Making & Paper Products (22);
	Printing and Recording Media Reproducing (23).
5. Chemical products	Chemical Materials & Products (26);
	Pharmaceutical (27);
	Chemical Fiber (28);
	Rubber Products (29);
	Plastic Products (30).
6. Non-metallic minerals	Nonmetallic Minerals Products (31).
7. Metals and metal products	Ferrous Metal Smelting and Rolling Procssing (32);
	Non-Ferrous Metal Rolling Processing (33);
	Metal Products (34).
8. Machinery	General Machinery Manufacturing (35);
	Special Machinery Manufacturing (36).
9. Transport equipment	Transportation Equipment Manufacturing (37).
10. Electronics	Electronic Machinery and Equipment (39);
	Electronic Communication Equipment and Computer (40);
	Instrument, Meter, Stationery and Office Machine (41).

Table 5: Descriptive statistics by industry

			Unweighted average							
Industry	Firms	Obs.	TFP growth[a]	Revenue[b]	Capital[c]	Standard labor[d]	Materials[b]	Sales effort[e]	Variable cost[f]	Prop. export
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1.Food	36631	157958	0.005	79.113	20.976	203	61.505	0.068	0.841	0.134
2.Textile	50518	217752	0.029	58.400	15.468	327	46.418	0.034	0.881	0.429
3.Furniture	13448	53571	0.031	41.903	10.072	180	33.047	0.051	0.857	0.245
4.Paper	15452	70305	0.027	52.366	25.538	197	39.973	0.043	0.849	0.0822
5.Chemical	53252	242213	0.030	78.809	30.728	222	61.659	0.059	0.840	0.185
6.Non-metal	27857	126065	0.039	48.957	23.770	249	36.529	0.062	0.825	0.113
7.Metals	31514	133910	0.023	157.140	57.822	326	128.912	0.037	0.874	0.208
8.Machinery	39540	176136	0.035	64.073	17.420	241	48.957	0.054	0.840	0.170
9.Transport	14980	67719	0.042	151.369	42.188	371	117.701	0.046	0.848	0.180
10.Electronics	35351	161767	0.037	161.957	30.302	342	133.005	0.056	0.847	0.318

[a] Growth of deflated revenue minus the growth of capital, labor and deflated materials weighted by the average cost shares between t and $t-1$ computed using a common cost of capital. During 1999-2008.

[b] Nominal. Millions of RMBs.

[c] Deflated by an investment price index. Millions of RMBs.

[d] Total wage bill / Average 2-digit firm's industry wage.

[e] Marketing cost / Cost of principal business.

[f] (Materials + Total wage bill) / Revenue.

Table 6: Model estimation, production function and productivity

Industry	Inputs			Polynomial in ω^*_{jt-1}		
	k (s. e.)	l (s. e.)	m (s. e.)	1st term (s. e.)	2nd term (s. e.)	3rd term (s. e.)
	(1)	(2)	(3)	(4)	(5)	(6)
1.Food	0.111	0.213	0.767	0.773	0.164	-0.007
	(0.011)	(0.020)	(0.014)	(0.157)	(0.019)	(0.001)
2.Textile	0.028	0.315	0.747	1.048	-0.179	-0.037
	(0.009)	(0.024)	(0.016)	(0.295)	(0.075)	(0.010)
3.Furniture	0.134	0.137	0.804	-0.286	0.137	0.001
	(0.031)	(0.048)	(0.052)	(0.612)	(0.084)	(0.005)
4.Paper	0.163	0.188	0.704	-0.259	0.431	-0.027
	(0.026)	(0.028)	(0.039)	(1.742)	(0.150)	(0.007)
5.Chemical	0.155	0.242	0.671	0.107	0.145	0.005
	(0.012)	(0.020)	(0.018)	(0.231)	(0.019)	(0.004)
6.Non-metal	0.062	0.228	0.830	0.375	-0.308	-0.045
	(0.005)	(0.013)	(0.011)	(0.188)	(0.048)	(0.005)
7.Metals	0.021	0.184	0.885	1.045	0.257	-0.015
	(0.008)	(0.014)	(0.009)	(0.368)	(0.041)	(0.009)
8.Machinery	0.103	0.261	0.751	1.423	0.168	-0.006
	(0.010)	(0.019)	(0.013)	(0.154)	(0.019)	(0.002)
9.Transport	0.180	0.260	0.631	0.849	0.212	-0.015
	(0.018)	(0.022)	(0.028)	(0.448)	(0.049)	(0.010)
10.Electronics	0.072	0.356	0.688	1.538	0.205	-0.002
	(0.011)	(0.031)	(0.018)	(0.258)	(0.025)	(0.006)

Table 7 Model estimation, demand shifters

	Sales effort							
	1st term	2nd term	3rd term	East	Middle	Capital city	Core	Export
Industry	(s. e.)	(s. e.)	(s. e.)	(s. e.)	(s. e.)	(s. e.)	(s. e.)	(s. e.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1.Food	5.003	-0.623	-2.000	0.079	0.097	-0.080	-0.018	-0.055
	(1.075)	(4.649)	(4.729)	(0.010)	(0.010)	(0.011)	(0.007)	(0.019)
2.Textile	-0.500	1.464	0.930	0.063	0.058	-0.002	-0.010	-0.075
	(0.905)	(10.394)	(14.051)	(0.012)	(0.013)	(0.008)	(0.004)	(0.017)
3.Furniture	7.680	-4.910	0.261	0.067	0.074	-0.070	-0.005	-0.103
	(2.268)	(14.664)	(15.829)	(0.033)	(0.036)	(0.023)	(0.013)	(0.035)
4.Paper	7.001	6.177	-39.081	0.065	0.117	0.008	-0.030	-0.056
	(1.651)	(14.087)	(16.419)	(0.029)	(0.035)	(0.018)	(0.021)	(0.046)
5.Chemical	4.626	1.720	-3.257	0.083	0.079	-0.006	-0.048	0.020
	(0.744)	(4.562)	(6.006)	(0.016)	(0.018)	(0.009)	(0.008)	(0.018)
6.Non-metal	5.465	-33.814	34.280	0.038	0.039	0.014	-0.015	-0.031
	(0.829)	(8.278)	(9.085)	(0.005)	(0.006)	(0.006)	(0.004)	(0.010)
7.Metals	2.647	-6.403	5.376	0.111	0.070	0.017	-0.006	0.007
	(1.395)	(11.351)	(9.883)	(0.011)	(0.013)	(0.006)	(0.006)	(0.013)
8.Machinery	4.287	0.420	-5.125	0.046	0.048	-0.011	-0.031	-0.020
	(0.965)	(7.620)	(12.774)	(0.010)	(0.011)	(0.006)	(0.005)	(0.010)
9.Transport	5.060	-11.535	5.446	0.072	0.073	0.011	-0.045	-0.016
	(0.844)	(7.058)	(12.736)	(0.014)	(0.020)	(0.011)	(0.010)	(0.019)
10.Electronics	-1.167	10.722	-10.588	0.028	-0.025	0.022	-0.013	0.003
	(0.867)	(6.538)	(5.644)	(0.016)	(0.018)	(0.008)	(0.007)	(0.019)

Table 8: Estimated productivity and markups

Industry	Prod. growth[a] (%)		St. dev.[b]		Levels 90/10[c]		Markup				Corr. Markup with	
	ω	Labor[d]	ω	Labor	ω	Labor	Mean	Q_1^a	Q_2	Q_3	ω^f	Labor[f]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. Food	4.725	8.565	1.150	1.113	7.130	16.692	1.172	1.071	1.123	1.211	0.842	0.204
2. Textile	3.677	8.045	0.590	0.803	3.165	7.019	1.136	1.055	1.098	1.167	0.725	0.207
3. Timber	3.965	8.176	1.077	0.877	7.745	8.704	1.137	1.062	1.105	1.172	0.902	0.176
4. Paper	5.177	8.705	1.056	0.920	6.707	9.507	1.125	1.055	1.093	1.153	0.852	0.251
5. Chemical	5.830	8.142	0.922	0.994	4.620	11.540	1.161	1.062	1.107	1.183	0.602	0.229
6. Non-metal	6.068	9.785	0.814	1.001	4.870	12.340	1.200	1.094	1.155	1.249	0.809	0.160
7. Metals	3.683	7.557	0.709	0.912	3.300	9.189	1.147	1.057	1.105	1.180	0.878	0.202
8. Machinery	6.136	8.827	0.888	0.905	4.794	9.045	1.167	1.071	1.123	1.206	0.796	0.281
9. Transport	5.848	8.935	0.896	0.950	6.417	10.079	1.128	1.057	1.096	1.158	0.768	0.218
10. Electronics	6.047	8.065	0.843	0.959	5.010	10.502	1.185	1.073	1.128	1.221	0.703	0.196

[a] Average log-growth.

[b] Standard deviation of log productivity.

[c] 90 percentile / 10 percentile of the level of productivity.

[d] Labor productivity is defined as Deflated value-added) / Labor.

[e] Quantiles of markups.

[f] Time average of each firm's productivity.

Table 9: Decomposition of productivity growth (%)

Industry	Aggregate growth		Survivors		Allocation		Entry[a]		Additions[b]		Exit	
	ω	Labor	ω	Labor	ω	Labor	ω	Labor	ω	Labor	ω	Labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. Food	7.780	19.745	9.493	24.148	0.190	0.056	-0.592	-2.233	-1.760	-2.900	0.449	0.674
2. Textile	7.762	19.344	9.122	21.648	1.437	2.754	-0.667	-1.479	-2.149	-3.973	0.019	0.395
3. Timber	6.584	21.094	9.740	25.654	1.295	-0.704	-1.613	-1.047	-3.236	-3.237	0.397	0.428
4. Paper	10.804	23.713	12.436	23.910	2.334	3.337	-1.357	-1.474	-3.313	-3.124	0.704	1.064
5. Chemical	14.517	22.407	13.830	22.044	2.420	3.920	-0.489	-1.431	-1.379	-2.882	0.134	0.756
6. Nonmetal	16.383	30.579	15.536	28.450	2.607	4.202	-0.438	-0.717	-1.624	-2.115	0.301	0.759
7. Metals	6.985	22.038	8.503	21.154	0.409	6.145	-0.544	-1.974	-1.394	-4.020	0.009	0.733
8. Machinery	16.859	27.230	15.621	25.427	2.886	4.485	-0.009	-0.659	-1.608	-2.400	-0.031	0.377
9. Transport	15.758	27.056	15.936	26.699	1.159	3.340	0.131	-0.966	-1.692	-2.449	0.224	0.433
10. Electronics	12.036	19.193	15.706	23.421	0.826	-0.172	-0.924	-1.723	-3.605	-2.958	0.033	0.625

[a] Firts show up in the sample and are 2 or less years old.

[b] First show up in the sample and are 3 years old or more.

Table 10: Median of Age distribution

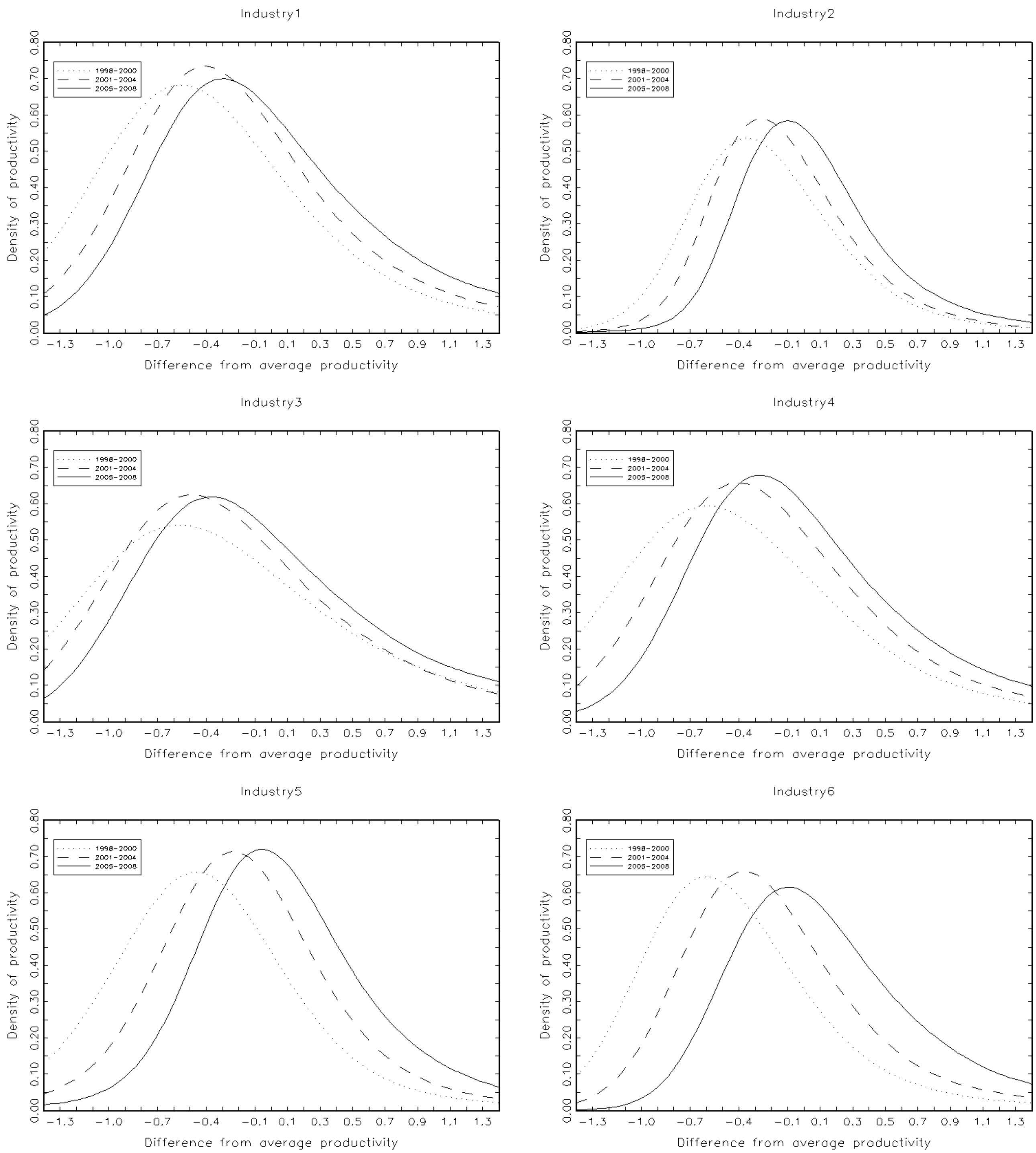
Industry	Whole sample						Entry and additions					Exit				
	98	00	02	04	06	08	00	02	04	06	08	98	00	02	04	06
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
All industry	7	8	8	6	6	6	3	3	3	2	2	6	8	8	5	6
1. Food	8	8	7	5	5	5	2	2	2	1	2	6	8	7	5	6
2. Textile	6	7	7	4	5	6	3	2	2	2	3	5	7	7	4	5
3. Timber	5	6	6	4	4	4	3	2	2	1	2	5	6	7	4	5
4. Paper	9	9	8	7	7	7	3	3	3	2	3	8	9	9	7	10
5. Chemical	7	8	8	6	6	6	3	3	3	2	3	6	8	7	6	6
6. Nonmetal	10	9	8	6	6	5	4	3	2	1	2	6	8	9	6	7
7. Metals	6	7	7	5	5	6	3	3	2	2	3	5	7	7	4	5
8. Machinery	13	12	9	6	6	6	5	3	3	2	3	9	10	10	5	7
9.Transport	9	8	8	6	7	6	3	4	3	2	3	6	8	8	6	7
10. Electronics	6	7	7	6	6	6	3	3	3	2	3	6	8	7	5	6

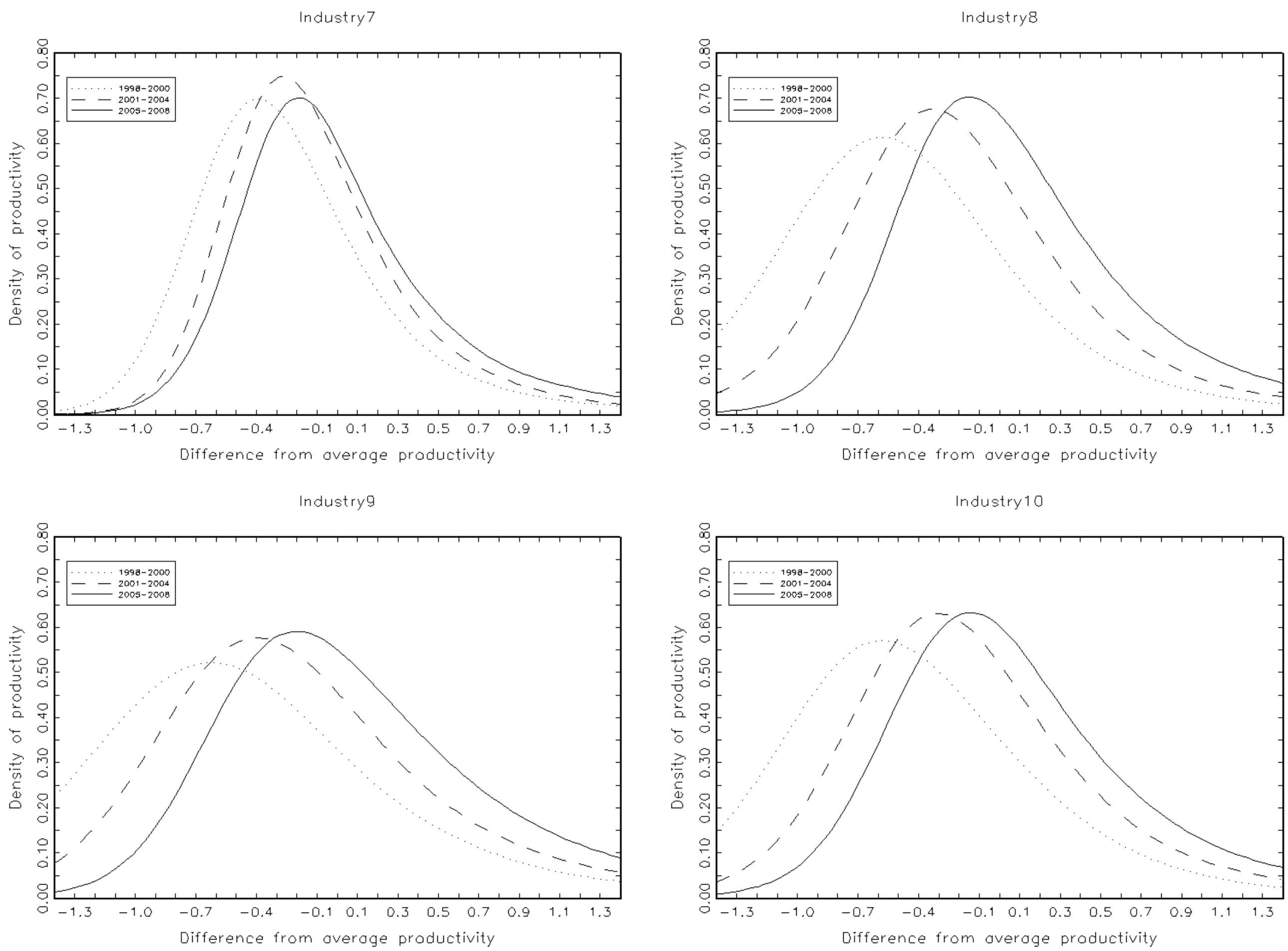
Table 11: Decomposition of survivor's productivity growth between young and old (%)

Industry	Contribution of young firms[a]					Ratio				
	00	02	04	06	08	00	02	04	06	08
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
All industry	3.915	2.862	4.163	4.842	5.837	56.785	50.050	57.515	73.734	77.307
1. Food	1.811	2.760	2.651	5.964	4.677	91.641	64.243	90.518	88.530	90.063
2. Textile	2.846	2.919	2.448	3.868	5.675	55.391	54.995	67.408	83.373	80.344
3. Timber	4.288	3.366	5.829	5.668	7.835	67.918	95.656	74.403	84.449	90.080
4. Paper	3.043	-0.684	3.899	4.250	4.327	49.620	-	46.974	69.088	70.312
5. Chemical	5.380	2.922	5.232	7.409	5.501	58.236	52.055	66.476	72.493	79.397
6. Nonmetal	4.158	3.572	4.846	6.473	5.905	54.078	44.606	57.212	68.546	79.403
7. Metals	2.968	3.293	2.966	1.781	6.808	63.642	57.785	61.190	96.195	74.692
8. Machinery	2.809	2.388	4.997	4.693	5.871	48.083	31.751	43.952	65.255	73.420
9. Transport	1.927	4.500	5.250	4.387	5.486	35.803	48.637	52.160	60.654	71.313
10. Electronics	8.227	3.325	4.702	3.135	6.782	57.947	49.174	51.317	67.709	70.470

[a] 8 or less years old.

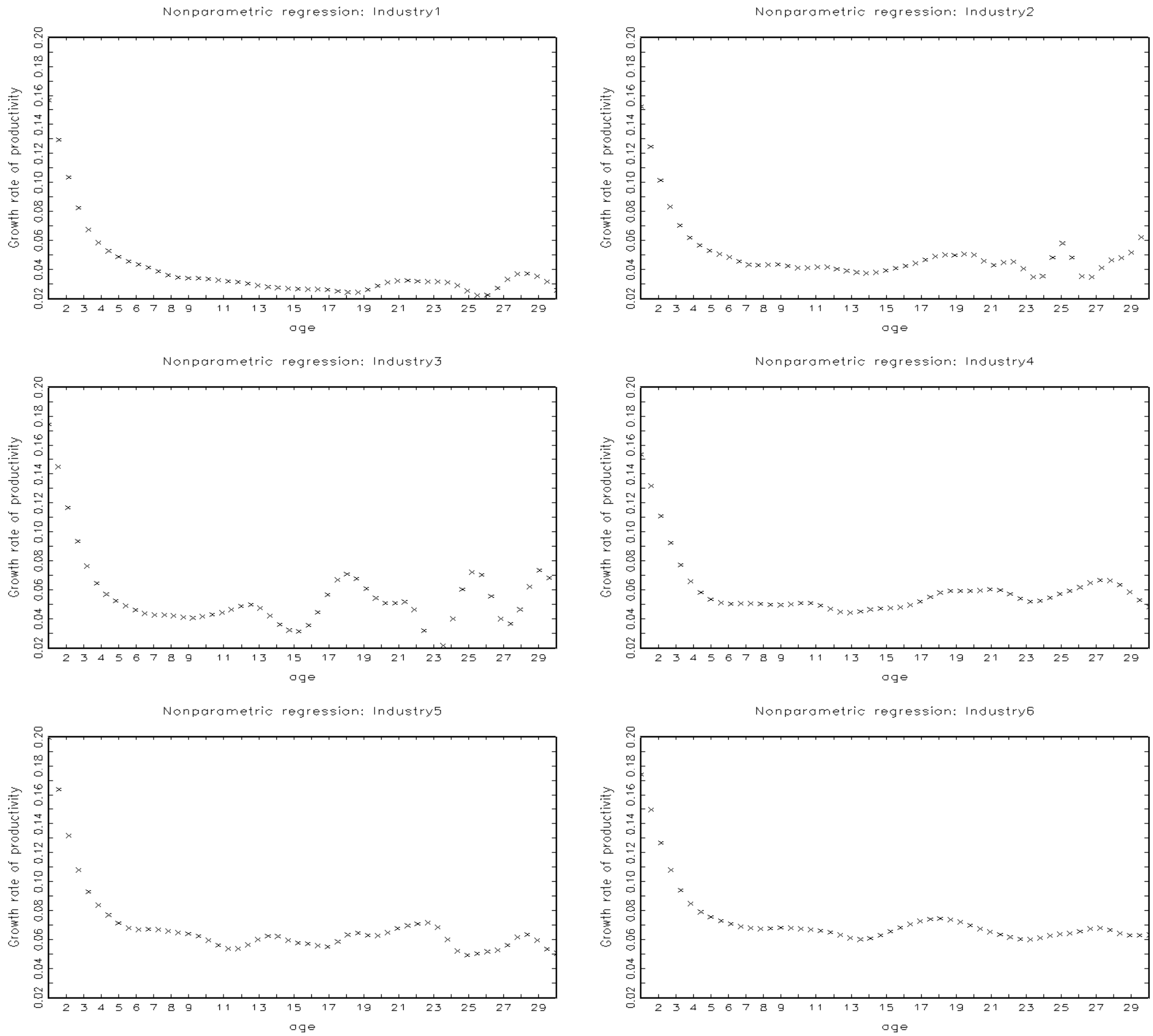
Figure 1: Distribution of estimated productivity

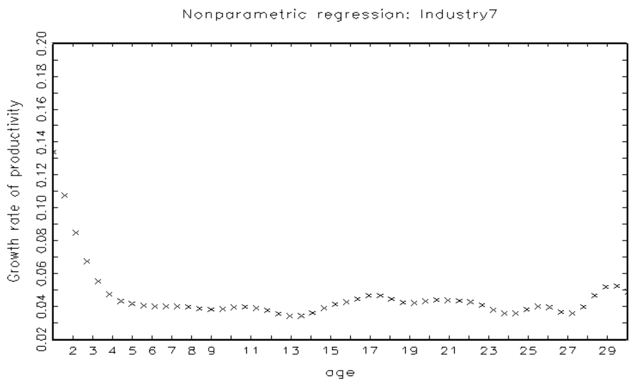


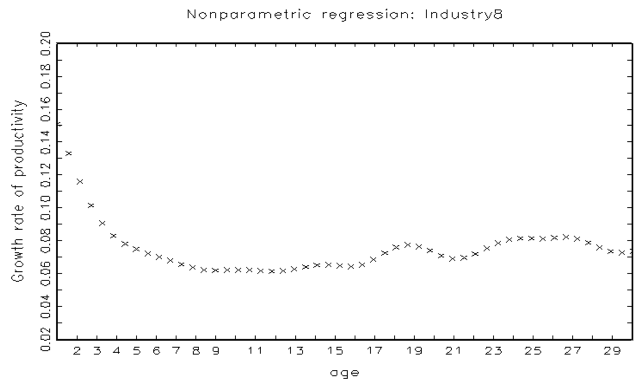


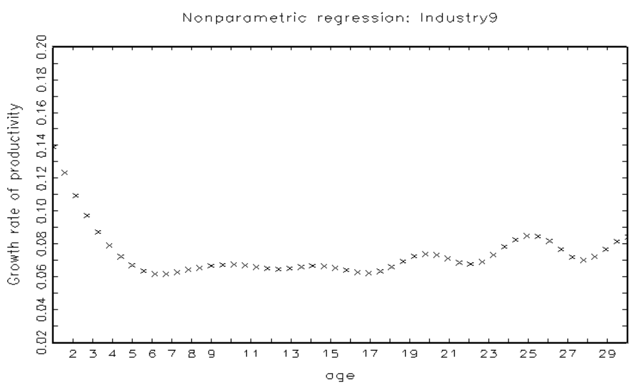
Industry7
Industry8
Industry9
Industry10
1998-2000
2001-2004
2005-2008
Density of productivity
Difference from average productivity
0.00
0.10
0.20
0.30
0.40
0.50
0.60
0.70
0.80
−1.3
−1.0
−0.7
−0.4
−0.1
0.1
0.3
0.5
0.7
0.9
1.1
1.3

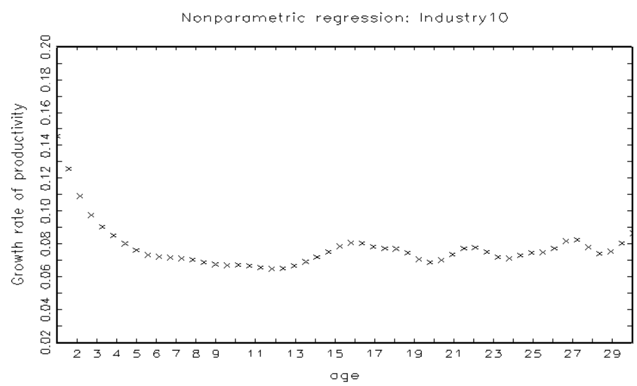
Figure 2: Nonparametric regression of productivity growth and firm age




Nonparametric regression: Industry7
Growth rate of productivity
age


Nonparametric regression: Industry8
Growth rate of productivity
age


Nonparametric regression: Industry9
Growth rate of productivity
age


Nonparametric regression: Industry10
Growth rate of productivity
age