An Application of the Melitz Model to Chinese Firms*

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Abstract

When the Melitz model is implemented in practice, the industrial productivity distribution is often assumed to be of Pareto form. In this case, a fundamental relationship $\kappa > \sigma - 1$ must hold to guarantee the convergence of the industrial average productivity, where κ is the concentration degree of the industrial productivity Pareto distribution and σ is the substitution elasticity across varieties in the industry. This paper estimates the concentration degrees of the Pareto distribution in industrial productivity and industrial substitution elasticities using firm-level data of 40 Chinese manufacturing industries from 1998 and 2007. However, the paper shows that the above fundamental assumption $\kappa > \sigma - 1$ does not hold for nearly all the industries for Chinese firm-level data. An explanation is proposed due to the distorted firm size and productivity for Chinese characteristics.

Keywords: Melitz model, Pareto distribution, productivity heterogeneity, export

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1 Introduction

The Melitz model developed in Melitz (2003),[1] has become a stepstone in the ”new” new trade theory and many other fields.[2] Among the many extended versions of the Melitz model is there one that assumes that industrial productivity follows a Pareto distribution $G_l(\theta)$, which we call **the Melitz-Pareto model**, whose form is as follows

$$G_l(\theta) = \begin{cases} 1 - \left(\frac{b_l}{\theta}\right)^{k_l} & \theta \geq b_l, \\ 0 & \text{else}, \end{cases} \tag{1}$$

where k_l is the concentration degree, and $b_l > 0$ is the lower bound of productivity distribution.

Many classic literatures adopt this form of productivity distribution in the practical application of the Melitz model, such as Antras and Helpman (2004, 2006), di Giovanni et al. (2011), Ottaviano (2011), etc. However, an assumption that $k_l + 1 > \sigma_l$ must be made under this assumption, [3] where σ_l is the substitution elasticity among varieties in industry l. Though it is clearly indicated that there are other *ex-ante* distributional assumptions[4], say Gamma distribution, the applicability of Pareto distribution in the Melitz model still need great attention in developing countries, in our case, China. This paper investigates whether the assumption of productivity Pareto distribution in the Melitz model can be applied to Chinese firms. Evaluating whether this assumption holds is important for the validity of the Pareto pre-assumption, especially due to the wide use of this model.

By comparing the estimates of above two parameters (k_l and σ_l) using Chinese firm level data, this paper shows that in most cases, k_l (estimated to be around 1) is much smaller than σ_l (ranging from 3 to 8) and concludes that the assumption that $k_l + 1 > \sigma_l$ does not hold and, the *ex-ante* Pareto distribution assumption cannot be verified with Chinese firms. Our empirical finding suggests that there are necessary pre-examinations for countries with in-perfect competition market and distorted firm productivity, such as China. Other distributions of industrial productivity shall be considered when applying the widely applied Melitz analytical framework to these countries.

Our paper relates to many existing literatures. First, the stylized facts of $k_1 + 1 > \sigma_l$ are valid in many empirical studies (mainly based on developed countries). For instance, the estimates of k_l are 8.28, 3.60 and 4.87 in Eaton and Kortum (2002), Bernard et al. (2003), and Eaton et al. (2011), respectively. All these estimates are for the U.S. firms. Our estimate of k_l is close to 1 which is very low comparing with above mentioned studies. Second, the literature has established that the power law exponent is close to 1, a phenomenon known as Zipf's Law, which implies that approximately, $k_l = \sigma_l - 1$. In di Giovanni et al. (2011) that our paper follows closely, the estimates of the power law exponent for French exporting and non-exporting firms separately are both close to 1. However, this inconsistence from the literature does not mean that the results in this paper are wrong. Instead, it is suggestive that China might have a different distribution function than those in developed countries which need to be carefully evaluated. To clarify our argument, this paper estimates exporting and non-exporting firms' (including all 40 industries) productivity and sales distributions with different TFP measurement methods. It is robust that the estimates of k_l are close to unit across different methods and sectors. This result is quite essential since if k_l is close to unit, it is almost for sure that $k_l+1 > \sigma_l$ cannot hold since σ_l is estimated greater than two in most literature. Further, consistent with the estimates of k_l , the estimates of the power law exponent are all around 0.4. Since the power law exponent is $\frac{k_l}{\sigma_l - 1}$, this result indicate that $k_l + 1 > \sigma_l$ cannot hold in China's case. The results that most of the estimates for estimated power law exponent to be lower in absolute value among exporting firms compared to the non-exporting ones are also consistent with di Giovanni et al. (2011).

Our strategy of realizing the **Melitz-Pareto** model is as follows. First, we estimate the production function of each industry (using four micro-econometric approaches, namely the pooled ordinary least square (OLS), Olley-Pakes (OP), Levinsohn-Petrin (LP), and firm fixed-effect model (FE)) based on the firm-level data from 1998 to 2007. Second, we compute each firm's productivity, and then estimate industrial productivity Pareto distribution, accordingly. Note that the size distributions of both non-exporting and exporting firms under the productivity Pareto distribution are also Pareto ones and their parameters are functions of parameters of those of industrial productivity distribution. We thirdly estimate parameters of these size distributions. Comparing these estimations with the parameters of the Pareto distribution of industrial productivity yields the substitution elasticities of varieties and fixed production cost. Combing the results obtained above shows that $k_l + 1 < \sigma_l$ for all industries.

2 The Melitz-Pareto framework

Suppose that there are two countries (i.e., the home country and the foreign country, denoted by H and F) in the economy. In the sequel, we denote the variable of the foreign country corresponding to that of the home country by adding a superscript "$*$". There are two factors (labor and capital) and M industries in each country, where there are N_l firms in industry l, with each producing a heterogeneous variety. Consumers in both countries are homogenous and the utility function of a representative consumer is $U = \prod_l \left(\int_0^{N_l} x_{li}^{\frac{\sigma_l - 1}{\sigma_l}} di \right)^{\frac{\beta_l \sigma_l}{\sigma_l - 1}}$, where β_l is the expenditure share of consumption, σ_l is the substitution elasticity between varieties in industry l, and x_{li} is the consumption of variety i in industry l for the consumer. If one lets the total expenditure be Y, then it is easy to find that the demand for variety i in industry l is

$$x_{li} = A_l p_{li}^{-\frac{1}{1-\rho_l}}, \tag{2}$$

where $\rho_l = \frac{\sigma_l - 1}{\sigma_l}$, $A_l = \beta_l Y P_l^{-\frac{\rho_l}{1-\rho_l}}$, and $P_l = \left(\int_0^{N_l} p_{li}^{\frac{\rho_l}{1-\rho_l}} di \right)^{\frac{1-\rho_l}{\rho_l}}$ is the ideal price index of industry l. We assume that firms in each industry in each country compete monopolistically. A potential firm must pay a fixed sunk cost F_l to enter industry l before observing its productivity θ, which follows a Pareto distribution $G_l(\theta)$. After it enters the industry, it needs to decide whether or not to start production in each period; this brings the firm another fixed production cost f_l. Hence, the profit of firm i in industry l in each period is

$$\pi_{li} = A_l^{1-\rho_l} \theta_{li}^{\rho_l} K_{li}^{\rho_l \alpha_l} L_{li}^{\rho_l (1-\alpha_l)} - r K_{li} - w L_{li} - f_l, \tag{3}$$

where θ_{li} is its productivity, K_{li} and L_{li} are the capital and labor hired, and r and w are prices of capital and labor in the economy. Plugging (2) into (3), solving the firm's profit maximization problem, and substituting its optimal pricing rule and output into $D_{li} = p_{li} x_{li}$ yields the firm's maximal domestic sale as

$$D_{li} \quad = \quad \rho_l^{\frac{\rho_l}{1-\rho_l}} A_l^{\frac{1}{1-\rho_l}} \omega_l^{-\frac{\rho_l}{1-\rho_l}} \theta_{li}^{\frac{\rho_l}{1-\rho_l}} = M_{jl} \Theta_{li}, \tag{4}$$

where

$$\omega_l = \left(\frac{r}{\alpha_l}\right)^{\alpha_l}\left(\frac{w}{1-\alpha_l}\right)^{1-\alpha_{jl}}, M_l = \rho_l^{\frac{\rho_l}{1-\rho_l}} A_l^{\frac{1}{1-\rho_l}} \omega_l^{-\frac{\rho_l}{1-\rho_l}},$$

are respectively the unit production cost and the measure of the domestic demand size in industry l, which is the same across all firms for each industry, and $\Theta_{li} = \theta_{li}^{\frac{\rho_l}{1-\rho_l}}$ measures the firm-specific productivity term. Following the same deduction procedures as those in Melitz (2003), it is clear that A_l is independent from θ_{li} in equilibrium. Moreover, the firm's maximal profit is

$$\pi_{li} = (1-\rho_l)D_{li} - f_l. \tag{5}$$

The firm operates the industry only if $\pi_{li} \geq 0$, which defines the minimum domestic sale $\underline{D}_l$ of the firm observed in the economy, as well as the productivity cut-off $\underline{\theta}_l$

$$\underline{D}_l = \frac{f_l}{1-\rho_l}, \underline{\theta}_l = \left(\frac{f_l}{(1-\rho_l)M_l}\right)^{\frac{1-\rho_l}{\rho_l}}. \tag{6}$$

Suppose firm i in industry l in the home country must pay a fixed cost κ_{li} before exporting to the foreign country. Moreover, there is an iceberg per-unit cost of $\tau_l > 1$ for export. Let the iceberg cost of domestic sales be normalized to be 1. Then it is easy to verify that foreign sales of firm i in industry l is $X_{li} = M_l^* \Theta_{li}$, where $M_l^* = \rho_l^{\frac{\rho_l}{1-\rho_l}} A_l^{*\frac{1}{1-\rho_l}} \omega_l^{*-\frac{\rho_l}{1-\rho_l}} \tau_l^{\frac{\rho_l}{1-\rho_l}}$ measures the foreign country's market size in industry l. Similarly, the export condition of firm i in industry l is $(1-\rho_l)M_l^*\Theta_{li} \geq \kappa_{li}$. Following Melitz (2003), we assume that κ_{li} is constant across firms in each industry l. Then there is a single exporting productivity cut-off, above which all firms export and below which none export.

2.1 *Pareto distribution of firms' domestic sales*

Suppose now G_l is a Pareto distribution of the form (1), where $b_l > 0$ is the lower bound, and $k_l > 0$ is the concentration degree of the productivity distribution, which vary with l. We use the firms' sales to represent their sizes. Then in autarky, the probability that the domestic sale of firm i in industry l is larger than a given quantity s is

$$\Pr(D_{li} > s) \;=\; \Pr\left(\theta_{li} > \left(\frac{s}{M_l}\right)^{\frac{1-\rho_l}{\rho_l}}\right) = \begin{cases} C_l s^{-\zeta_l} & D_{li} \geq \underline{D}_l, \\ 0 & D_{li} < \underline{D}_l. \end{cases} \tag{7}$$

where $C_l = \left(M_l^{\frac{1-\rho_l}{\rho_l}} b_l\right)^{k_l}$, $\zeta_l = \frac{(1-\rho_l)k_l}{\rho_l}$. (7) implies that the domestic sale D_{li} of firm i in industry l in the home country follows a Pareto distribution with exponent ζ_l. Moreover, the Pareto exponents ζ_l varies by industry.

2.2 *Pareto distribution of firms' exports*

The distribution of foreign sales for exporting firms is different from Equation (7). To see this, we only consider industry l according to symmetry. For simplification, we assume that there is $\kappa_{li} = \kappa_l$ for all firms in industry l. Then the profit of firm i in industry l under openness is

$$\pi_{li} \;=\; \pi_{li}^D + \pi_{li}^X,$$

where π_{li}^D is its profit from domestic sale, and π_{li}^X is its profit from exporting to the foreign country. Obviously, there is $\pi_{li}^X = \max\{0, (1-\rho_l)M_l^*\Theta_{li} - \kappa_l\}$. Then firm i exports to the foreign country only if $(1-\rho_l)M_l^*\Theta_{li} \geq \kappa_l$, or $X_{li} = M_l^*\Theta_{li} \geq \frac{\kappa_l}{1-\rho_l} = \underline{X}_l$. This implies the probability that the foreign sale of firm i in industry l is larger than a given quantity s is that

$$\Pr(X_{li} \geq s) \;=\; \begin{cases} C_l^* s^{-\zeta_l} & s \geq \underline{X}_l, \\ 1 & s < \underline{X}_l. \end{cases} \tag{8}$$

where $C_l^* = \left((M_l^*)^{\frac{1-\rho_l}{\rho_l}} b_l\right)^{k_l}$ and ζ_l is defined above as $\frac{(1-\rho_l)k_l}{\rho_l}$. Moreover, the export productivity cutoff is $\underline{\theta}_{Xl} = \left(\frac{\kappa_l}{(1-\rho_l)M_l^*}\right)^{\frac{1-\rho_l}{\rho_l}}$.

2.3 *Fixed sunk costs with international trade*

The **Melitz-Pareto** model considers only steady state equilibria in which the aggregate variables remain constant over time. In the steady equilibria, each firm's productivity level does not change over time, and thus its' per-period profit level (excluding F_l) will also remain constant. Let the equilibrium distribution of incumbents' productivity be $\mu_l(\theta)$ and that of exporters be $\mu_{Xl}(\theta)$. Then their distributions are of the following:

$$\mu_l(\theta) = \begin{cases} \frac{g_l(\theta)}{1-G_l(\underline{\theta}_l)} & \theta \geq \underline{\theta}_l, \\ 0 & \text{else}, \end{cases} \quad \text{and} \quad \mu_{Xl}(\theta) = \begin{cases} \frac{g_l(\theta)}{1-G_l(\underline{\theta}_{Xl})} & \theta \geq \max\{\underline{\theta}_l, \underline{\theta}_{Xl}\}, \\ 0 & \text{else}. \end{cases}$$

Here is made the following implicit hypothesis.

Hypothesis 1 *For each industry l, the parameters in the productivity distribution satisfies $k_l + 1 > \sigma_l$.*

If **Hypothesis** 1 holds, the average productivity level $\tilde{\theta}_l$ of incumbents in industry l is a function of the cut-off productivity level $\underline{\theta}_l$ according to $\mu_l(\theta)$, and the one $\tilde{\theta}_{Xl}$ of exporters is a function of $\underline{\theta}_{Xl}$ according to $\mu_{Xl}(\theta)$:

$$\tilde{\theta}_l(\underline{\theta}_l) = \left(\frac{k_l}{k_l + 1 - \sigma_l}\right)^{\frac{1-\rho_l}{\rho_l}} \underline{\theta}_l, \quad \tilde{\theta}_{Xl}(\underline{\theta}_{Xl}) = \left(\frac{k_l}{k_l + 1 - \sigma_l}\right)^{\frac{1-\rho_l}{\rho_l}} \underline{\theta}_{Xl}, \tag{9}$$

where $\sigma_l = \frac{1}{1-\rho_l}$ is the substitution elasticity of varieties in industry l. If this hypothesis is broken, then the average industrial productivity $\tilde{\theta}_l(\theta_l) = +\infty$, and thus industrial average net profit and finally industrial fixed sunk cost, are all infinite, which implies that the successive deduction of the **Melitz-Pareto** model can not be carried out. In the sequel, we will estimate both k_l and σ_l for each industry l using Chinese firm-level data set, and we will show that **Hypothesis** 1 does not hold for Chinese firms and that, therefore, *the* **Melitz-Pareto** *model is not applicable to Chinese firms with assumption of industrial productivity Pareto distribution.*

Summarizing the above discussions, we see that **Hypothesis** 1 is important for the successive deduction in the **Melitz-Pareto** model. We can test whether it holds by estimating b_l, k_l and ρ_l. As will be shown in the sequel, they can be estimated from the power law distributions of industrial productivity distributions, domestic sales of non-exporters and foreign sales of exporters. To verify above hypothetical intuition, the following econometric estimates are conducted with Chinese firm-level data.

3 Econometric approach

3.1 *Estimation of productivity distributions of industries*

We introduce the estimation approach of industrial productivity distributions in this section.

There production function for firm i in industry l in year t is $Y_{lit} = \theta_{li} K_{lit}^{\alpha_l} \mathcal{M}_{lit}^{\gamma_l} L_{lit}^{\varrho_l}$, where θ_{li} is the productivity level observed after it pays the industry-specific fixed sunk cost F_l, which follows a Pareto distribution of the form (1), where L_{lit}, K_{lit} and $\mathcal{M}_{lit}$ are labor, capital and intermediate input used in production and Y_{lit} is the output. [5] Suppose $\alpha_l, \gamma_l, \varrho_l$ are estimated for each industry l, then each firm's productivity level is $\theta_{li} = \frac{Y_{lit}}{K_{lit}^{\alpha_l} \mathcal{M}_{lit}^{\gamma_l} L_{lit}^{\varrho_l}}$. This implies that we can estimate the productivity distribution $G_l(\theta)$ for each industry l. Let the vector sorted from the productivity vector $\theta_l^t = (\theta_{l1}^t, \cdots, \theta_{lN_l^t}^t)^T$ in year t in descending order be $\tilde{\theta}_l^t = (\tilde{\theta}_{l1}^t, \cdots, \tilde{\theta}_{lN_l^t}^t)^T$, where θ_{lk}^t is the productivity level of firm k in industry l. Denote the number of firms whose productivity is larger than $\tilde{\theta}_{lk}^t$ by N_{lk}^t. Then we can approximate $1 - G_l(\tilde{\theta}_{lk})$ by $\frac{N_{lk}^t}{N_l^t}$, where N_l^t is the number of incumbents in industry l. We thus have

$$\ln \frac{N_{lk}^t}{N_l^t} = \xi_l - k_l \ln \tilde{\theta}_{lk}^t, \forall t, \tag{10}$$

where $\xi_l = k_l \ln b_l$. The effects are included in the estimation of (10).[6] This method makes use of the definition of a Pareto distribution, and it is applied by Axtell (2001) and di Giovanni et al. (2011). We follow Gabaix and Ibragimov (2011)'s estimation strategy in practical operations.

3.2 *Estimation of the distributions of firms' domestic sales and exporting sales*

We first illustrate the estimation approach for domestic sales of non-exporters in industry l. Let $D_l = (D_{l1}, \cdots, D_{lN_l})^T$ be the vector of domestic sales of the N_l firms in industry l. Note that the distribution of D_{li} without international trade is Pareto with cumulative distribution function $\Phi(D) = 1 - C_l D^{-\zeta_l}$, where $\zeta_l = \frac{(1-\rho_l)k_l}{\rho_l}$. Then we can estimate ζ_l as follows. First we sort the vector $D_l^t = (D_{l1}^t, \cdots, D_{lN_l^t}^t)$ in year t in descending order to yield the new vector $\tilde{D}_l^t = (\tilde{D}_{l1}^t, \cdots, \tilde{D}_{lN_l^t}^t)^T$, where D_{lk}^t is the domestic sale value of firm k in industry l. Denote the number of firms whose sales are larger than D^t_{lk} by N^t_{lk}. Then we can apply $\frac{N^t_{lk}}{N^t_l}$ to approximate $1 - \Phi(\tilde{D}^t_{lk})$. We thus have

$$\ln \frac{N^t_{lk}}{N^t_l} = \chi_l - \zeta_l \ln \tilde{D}^t_{lk}, \tag{11}$$

where $\chi_l = \ln C_l$, i.e, $C_l = e^{\chi_l}$.

For estimation of the distribution of foreign sales of exporting firms, we let the vector of their foreign sales in year t in industry l be $X^{Xt}_l = (X^{Xt}_{l1}, \cdots, X^{Xt}_{ln^t_l})^T$, where n^t_l is the number of incumbent exporters in year t in industry l and X^{Xt}_{lk} is the sale of exporter k. Note that X^{Xt}_{lk} follows the Pareto distribution with cumulative distribution function $\Psi(X) = 1 - C^*_l X^{-\zeta_l}$ from (7), where $C^*_l = ((M^*_l)^{\frac{1-\rho_l}{\rho_l}} b_l)^{k_l}$. Let the vector sorted in decending order from X^{Xt}_l be $\tilde{X}^{Xt}_l = (\tilde{X}^{Xt}_{l1}, \cdots, \tilde{X}^{Xt}_{ln_l})^T$. Then, in a similar way, we know that we can estimate C^*_l and ζ_l by regressing the following equation:

$$\ln \frac{N^t_{lk}}{n^t_l} = \psi_l - \zeta_l \ln \tilde{X}^{Xt}_{lk}, \tag{12}$$

where N^t_{lk} is the number of firms whose sales are larger than $\tilde{X}^{Xt}_{lk}$ and $\psi_l = \ln C^*_l$ or $C^*_l = e^{\psi_l}$.

Note that (11) and (12) are different only in the intercepts. Therefore, we can regress them simultaneously for each industry, controlling the time fixed effects.

3.3 *Cut-offs of domestic sales of non-exporters and foreign sales of exporters*

We estimate cut-offs of domestic sales of non-exporters and foreign sales of exporters as follows. We find the minimum domestic sales and foreign sales of non-exporters and exporters, respectively, in each year for this industry and then calculate their means over all periods. These estimators are unbiased from the true values as the data set covers the population of all firms.

3.4 *Computation of other variables*

Suppose that we have estimated $\xi_l, k_l, \chi_l, \psi_l, \zeta_l, \underline{D}_l$ and $\underline{X}_l$. Then the other parameters are calculated as follows:

$$b_l = e^{\frac{\xi_l}{k_l}}, \rho_l = \frac{k_l}{k_l + \zeta_l}, C_l = e^{\chi_l}, C_l^* = e^{\psi_l}, \tag{13}$$

and

$$f_l = (1-\rho_l)\underline{D}_l, \kappa_l = (1-\rho_l)\underline{X}_l, M_l = \left(\frac{C_l^{1/k_l}}{b_l}\right)^{\frac{\rho_l}{1-\rho_l}}, M_l^* = \left(\frac{(C_l^*)^{1/k_l}}{b_l}\right)^{\frac{\rho_l}{1-\rho_l}}, \tag{14}$$

as well as

$$\underline{\theta}_l = \left(\frac{f_l}{(1-\rho_l)M_l}\right)^{\frac{1-\rho_l}{\rho_l}}, \underline{\theta}_{Xl} = \left(\frac{\kappa_l}{(1-\rho_l)M_l^*}\right)^{\frac{1-\rho_l}{\rho_l}}, \varsigma_l = \left(\frac{\underline{\theta}_l}{\underline{\theta}_{Xl}}\right)^{k_l}. \tag{15}$$

Finally, according to (**??**), the industrial fixed sunk cost F_l can be achieved as follows

$$F_l = \frac{\sigma_l - 1}{k_l + 1 - \sigma_l} \frac{f_l + \varsigma_l \kappa_l}{\delta_l} \left(\frac{b_l}{\underline{\theta}_l}\right)^{k_l}. \tag{16}$$

4 Data descriptions

4.1 *Data set and Coverage*

This paper employs plant-level data from the Annual Survey of Industrial Firms (**ASIF**) cross-sectional data collected by the National Bureau of Statistics of China between 1998 and 2007. The data set contains detailed information (including more than 100 financial variables listed in the main accounting sheets of these firms) for all state-owned and non-state firms above a designated scale (above 5 million RMB) in (1) mining, (2) manufacturing, and (3) production and distribution of electricity, gas and water, with 40 industries indexed from 6 to 46 and industry 38 vacant (see Table 1 in Sun et al. (2011) for the industry codes, industry names and their abbreviations). The number of firms covered by this data set is 161,000 in 1998 and 336,768 in 2007, respectively. The industry section of the China Statistical Yearbook and reports in the China Markets Yearbook are compiled and based on this data set (Lin et al. 2009; Lu and Tao 2009; Brandt et al.

2012). The data set explored in this paper covers every firm's output value, value added, capital stock, labor hired, intermediate input, domestic sale value, exporting sale, scale type, exporting status, operational status, ownership, age, etc., between 1998 and 2007, in each industry.

The ASIF data set provides us with a unique opportunity to observe Chinese enterprises performance with a large and comprehensive sample. The time duration also enables us to avoid some radical economic policy changes in the early and middle 1990s (structural change, SOE reform, etc.). China has undertaken a series of economic policy reformd since 1978, and such structural adjustments stabilized in the later years. Especially in the late 1990s, more and more domestic firms and plants are emerging and competing with their foreign counterparts for the unconditional government fiscal loans, abolishing industrial licensing, equalizing foreign direct investment opportunities, cutting import duties, deregulating capital markets and reducing tax rates. Therefore, the time period of this data set–with relatively stable price indices and deflators for all variables–is suitable to indicate the firm performance with specific effects.

Some noteworthy drawbacks in the ASIF data set need further discussions. We believe these characteristics are partially responsible for causing the estimates' standard errors to be comparatively large and result in less convergence in our later empirical tests. The first is that the number of manufacturing firms covered in the sample period increased dramatically since 2004. Apart from more and more firms having annual sales reaching the official statistical category, the year 2004 was an industry census year and there was more comprehensive survey coverage in that year, which may explain the jump in the number of firms from 2003 to 2004 (Lu and Tao 2009). The second is that the ASIF does not cover small non-state-owned firms with annual sales of less than five million yuan, which could cause the sample estimation to be upwardly biased. The third and most challenging problem is that the ASIF does not provide organization relation information among multi-plant firms. We could only recognize the individual plants and had to ignore the situation that saw enterprises having more than one plant in different regions. The disaggregate composition of plant total productivity did not allow for a review of some multi-plant firms real performance.

As the data set contains some noisy and misleading samples, and also because of our special research objectives, we deal with the data set in the following way. (1) Following Jefferson and Zhang (2008), we drop those observations whose key financial variables (such as total assets, net value of fixed assets, sales and gross value of industrial output) are missing and have fewer than 10 employees. (2) Following Cai and Liu (2009) and guided by the General Accepted Accounting Principles, we drop those observations whose total assets are less than their liquid assets, those whose total assets are less than the net value of their fixed assets, those whose identification numbers are missing or not unique and those whose establishment time is invalid. (In particular, the establishment time shall not be earlier than 1840 and shall not be later than 2007.) (3) We drop those observations whose sales, total assets and values of fixed assets are less than 5 million yuan. (4) As intermediate inputs are important for firms' production, and also because we apply the OP approach and the LP approach to compute firms' productivity, we drop those observations whose investments or intermediate inputs are zero. After the above rigorous filter, we finally obtain a total of 407,919 observations from the original sample of 2,400,000. All nominal terms are originally measured in current Chinese yuan. We thus use the GDP deflator to convert the nominal terms (gross output value, net sales of the plants, investment, intermediate inputs and all other monetary variables) into real ones by choosing 1978 as the base year.

Apart from above treatment, we are facing one critical problem regarding the endogeneity issue of firm behavior. Previous studies using the **ASIF** data set all include observations with negative or zero investment and intermediate input values, and their total observations are over 2,400,000 (we have 169,902 firms and 407,919 observations in our 10-year data set, which is one-sixth of untrimmed ASIF data set). We are arguing that if researchers need to observe firms' endogenous behavior, henceforth they should estimate their self-adjustments in capital and labor investment and yearly intermediate inputs from year to year, and that zero investments or intermediate inputs are intolerable. Since we assume that firms are aware of their productivity changes, as well as their profitability, there is less solid ground to assume they have static decision making in each year's production decision making. Though Levinsohn and Petrin (2003)'s proposed method on firm-level productivity estimation only requires intermediate input information, we still need to compare different estimation methods of firm productivity in order to establish our robust results. Such trade-offs lead to a large quantity of data loss in our actual empirical test (Pooled OLS, FE, OP and LP methods accordingly). However, it enables us to compare different methods with the same background. The samples with/without investments and intermediate inputs are summarized in Table 1 in the **Appendix**.

4.2 *Variable definitions*

The variables we use in this paper are, respectively, value-added, total sales, labor hired, capital stock, intermediate input and exporting sales. The data of each firm in each industry from 1998 to 2007 is obtained after being dropped. A firm's domestic sales is measured as the difference between the firm's total sales and its foreign sales. Its capital stock is measured as the net value of fixed assets at the end of each year, and its quantity of labor hired is measured as that of its average employees within a year. A firm's productivity is measured by total productivity . In this paper, we apply four methods (i.e., OP, LP, Pooled OLS and FE) to compute each firm's productivity using 10-year of non-balanced panel data.

The measure of capital stock here is different from the commonly used Perpetual Inventory Method. In the interest of uniformity, and for obtaining comparable results, Olley and Pakes (1996) and Levinsohn and Petrin (2003) proposed some alternative methods for estimating capital stock (capital stock of current year is defined as the gross fixed assets of the last year minus the depreciation over the last year). Due to variation in the capital stock measurements, and the fact that some required information for the early years (industrial price depreciation rate, investment and intermediate input level, and industrial gross fixed assets) are not available, this paper uses the net sum of fixed capital (in the data set, it is defined as the previous year's fixed capital minus current year investment and other intermediate inputs) deflated by the price deflators.

The descriptive statistics for all variables, for all industries and for the whole time period are provided in Table 2 in the **Appendix**.

5 Estimation results

5.1 *Productivity distribution*

As intermediate inputs are important for practical production, we adjust the industrial production function as $Y_{lit} = \theta_{lit} K_{lit}^{\alpha_l} \mathcal{M}_{lit}^{\gamma_l} L_{lit}^{\varrho_l}$ for each l, where $\alpha_l + \gamma_l + \varrho_l = 1$, $\mathcal{M}_{lit}$ is the intermediate input used for production,[7] and α_l, γ_l and ϱ_l are output elasticities of capital, intermediate input and labor in industry l. We apply four approaches (i.e., Pooled OLS, FE, OP, and LP), to estimate the industrial production functions (see the **Appendix** for a description of these methods). We find that the three inputs–labor, intermediate input and capital–are almost significant at the 10 percent level for all industries. As well, the null hypothesis $H_0 : \alpha_l + \gamma_l + \varrho_l = 1$ holds significantly at 10 percent for almost all industries.[8]

After α_l, γ_l and ϱ_l have been obtained, we solve θ_{lit} for each firm in each industry in each period t from the result of production function estimated using each approach. We then estimate k_ls and ξ_ls in industrial productivity distributions by regressing (10) using the method proposed in Subsection 3.1, controlling the time fixed effects.[9] We then calculate b_l by e^{ξ_l/k_l}. [10] The results based on the estimated productivity using FE and LP are somewhat similar. The correlation coefficient between $k_l(b_l)$ estimated based on FE and LP is 0.84 (0.58). However, the results estimated using FE/LP and Pooled OLS/OP are much different. The correlation coefficient between $k_l(b_l)$ estimated based on FE and Pooled OLS is 0.12 (-0.13). That between $k_l(b_l)$ estimated based on FE and OP is 0.43 (0.12). This implies that different approaches yield different productivity distribution results.[11] In the following discussion, we only apply the result estimated using FE. Our rationale is as follows. First, Pooled OLS is biased because of simultaneity and endogeneity (Olley and Pakes 1996). Second, the ideas of LP and OP are not consistent with the Melitz model that assumes that a firm's productivity, if it is in the market, remains constant in the stationary dynamics, even though it may exit the market at a constant probability. The idea of FE essentially assumes that the logarithm of productivity θ of a firm in the stationary equilibrium follows a random walk (i.e., $\ln \theta_{t+1} = \ln \theta_t + \varepsilon_{t+1}$, where ε_t are i.i.d. random variables and t represents period). From this point of view, FE is the most consistent with the thought in the Melitz model.

5.2 *Distribution of domestic sales of all the incumbents and non-exporting firms and heterogeneity preferences*

We then estimate ζ_ls of the distributions of domestic sales of non-exporters and exporters in each industry. [12] According to the theoretical result given in Section 3, the two ζ_ls estimated applying data of non-exporters and exporters in each industry shall be the same. However, the correlation coefficient between these two estimation results for all the industries is only 0.43, which implies their large difference. Further tests show that the absolute value of ζ for non-exporters is strictly larger than that for exporters. One reason is that we ignore the influences of the regions where the firms are located, as well as many other complicated economic and non-economic factors on the distribution of domestic sales of firms.[13] One is that industrial exporting fixed cost is heterogeneous across firms, as shown in Schmitt and Yu (2001); Schroder and Jorgensen (2008); di Giovanni et al. (2011); Jorgensen et al. (2012), etc. Another is that productivity distributions of non-exporters and exporters are different, as shown in Sun and Zhang (2011). This result implies that we may need to change either the assumptions of homogeneous fixed exporting costs across firms or the same productivity distribution between non-exporters and exporters in the same industry when applying the Melitz model to Chinese firms. In this paper, to keep consistent with the former sections, we still maintain these assumptions. Thus, we make the joint-regressions for non-exporters' domestic sales and exporters' foreign sales proposed in Section 3 and get the same ζ_l for both types of firms. The result is shown in Table 3. It shows that Pareto distribution parameters change in this case, which further indicates that the above-mentioned explanations may hold in practice. We test whether $H_0 : \zeta_l > 1$ holds or not for its estimated value in each industry in Table 3, respectively. The testing results show that the null hypothesis H_0 does not hold for all cases, which unfolds a consistent and robust result, i.e., $\zeta_l > 1$. This implies that Hypothesis 1 does not hold for each industry l (i.e., $k_l + 1 > \sigma_l$). [14]

5.3 *Explanation of the results*

The above empirical estimates indicates that the Melitz model can not be applied to Chinese firms together with the assumption of productivity Pareto distribution. Here we are more interested in the intuitive explanations on why China is so different from developed countries and why the distribution of firms' productivity and sizes in China is less dispersed?

From our point of view, the size and productivity distributions of Chinese firms are so different from those in developed countries because the institution in China is incomplete and there is too much distortion in China, which influences the efficiency of resource allocation across firms.

First, the absence of property protection in China yields the "Greshams law". Less efficient firms enter into the market and produce by stealing or copying the brands of high efficient firms, which cost the latter much to invest, research and develop them. The former firms exhaust the brand rents of the latter ones with very low costs and finally drive them out of markets. In developed countries, the situation is different. This also explains why the productivity and size distributions of the (survived) Chinese firms are less dispersed.

Second, the administrative distortion caused by the ”inter-county competition” (which is commonly considered as the underlying mechanism promoting the rapid growth of China economy) distorts the true operation costs of various firms. To gain rapid GDP growth, finance and taxation incomes, and high employment ratios, local governments in China attract and bid for investments via various favorable policies, which include subsidies, tax reimbursements, exemption, refunds of taxes, lowering land prices, etc. These policies result in many rent seeking behaviors and also market segmentation. They also lead to less efficient firms to enter into the markets and force those high-productivity firms who are not familiar with these behaviors to exit the industries. These policies also reduce firms' innovation motives that can improve their productivity. The final synthetical effect is that the industrial productivity and size distributions are different from those in developed countries, which are also less dispersed.

Third, the industrial monopoly caused by government intervention reduces the efficiency of resource allocation across industries and firms. There are many entry and exit barriers set by the central or the local governments, whose aim is to protect the benefits of state-owned enterprises. These barriers prevent many high-productivity firms to enter many industries, which are considered to ”matter vital to national well-being and the people's livelihood” and thus protect less-efficiency state-owned firms. These firms receive direct and indirect preferential policies in the domestic market competition. Such local protectionism offers ”zombie” factories or low-productivity firms of high surviving opportunities. They thus have no incentives to improve their productivity and their productivity and sizes are very similar. The other too many firms have to enter into some unrestricted industries to compete to survive, which results in excessive competition and less dispersion in industrial productivity distributions in them. The final effect is that the size and productivity distributions of Chinese firms are different from those in developed countries and they are less dispersed.

Another possible reason is that there is heterogeneity of fixed exporting costs across firms, which interacts with heterogeneity of firm productivity. The heterogeneity of fixed exporting costs across firms was introduced to international trade modeling first in Schmitt and Yu (2001) to explain why firms' exporting behaviors are so different. Since then, there are much development about this topic, such as Jorgensen et al. (2012); Schroder and Jorgensen (2008). Some research shows that the heterogeneity of fixed exporting costs may be more important to explain heterogeneity of firms' exporting behaviors. di Giovanni et al. (2011) applied this concept to explain the difference between size distributions of non-exporters and exporters. If there's heterogeneity among firms fixed exporting costs,[15] then there will be estimation bias in parameters of firm productivity and size distributions and then the relationship among ζ_l, κ_l, ρ_l shown in (13) does not hold.

6 Conclusion

We estimate the **Melitz-Pareto** model using the statistical database of Chinese industrial enterprises above the designated size in 40 manufacturing industries between 1998 and 2007. It shows that an underlying hypothesis that guarantees the convergence of average industrial productivity level in this framework does not hold in Chinese firm-level data. This implies that the Melitz-Pareto model may not apply to China's case. An explanation is proposed to illustrate why firms in China are so different from those in developed countries.

Our result suggestively implies that we shall be careful to assuming productivity distribution when empirically apply the Melitz model to China (and other developing countries). There shall be necessary pre-examinations for firms' productivity and size distributions in countries with in-perfect competition markets and much distortion. Otherwise, the pre-assumed setting could violate the validity of comparison among nations of various kinds, or the industrial, firm productivity difference analysis.

Future work is to develop a model to implement the mechanism which results in the inapplicability of the Melitz-Pareto model to Chinese firms. We are sure that it will lead to fruitful insights on distortion, firms' size and productivity distributions, and resource allocation.

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Notes

[1]There are many antecedents. Montagna (1995) presents a monopolistic competition model with heterogeneous marginal costs in the Dixit-Stiglitz framework seminared by Dixit and Stiglitz (1977) for a closed economy. Jean (2002) extended this setting to an open economy with fixed exporting costs and thus is very alike to the Melitz model in terms of mechanism and results. Following another line of firm heterogeneity, Schmitt and Yu (2001) proposed a Melitz-like model with firms-specific fixed costs rather than marginal costs.

[2]Another one is Bernard et al. (2003). However, They are essentially different in market structure and entry barrier.

[3] In fact, this assumption is implicitly made in the above-mentioned literatures. Their explicit assumption is $k_l > 2$, while the former is critical and the latter is not.

[4]Eaton (2011) provides explicit footnotes on the merits of Pareto distribution and discussion of other distributional features of heterogenous firm model in application.

[5]According to Melitz (2003), the productivity of each firm in every industry does not vary with time. Moreover, the productivity distribution of each industry does not vary with time.

[6]In Giovianni et al. (2010), two other methods are applied to estimate a Pareto distribution. One is to estimate its density function; the other is to estimate a similar equation $\ln\left(N_{lk} - \frac{1}{2}\right) = \varrho_l + k_l \ln \theta_{lk}$ like (10), which is proposed by Gabaix and Ibragimov (2011). Gabaix and Ibragimov (2011) also prove that k_l has a standard error of $|k_l|(N_l)^{-1/2}$ for this method. Generally, the three methods yield very similar results when the sample scale is sufficiently large.

[7]The form of production function assumed here does not conflict to that assumed in (3) if only we consider the capital $\mathcal{K}$ there as the composition of the capital K and the intermediate input $\mathcal{M}$. Specifically, $\mathcal{K} = K^{\frac{\alpha}{1-\varrho}} \mathcal{M}^{\frac{\gamma}{1-\varrho}}$. Then the industrial function can be rewritten as $Y_{lit} = \mathcal{K}_{lit}^{1-\varrho_l} L_{lit}^{\varrho_l}$.

[8]We did not report them here to save space. The estimation results of industrial production functions for 40 manufacturing industries based on FE, LP, Pooled OLS and OP can be found in Table 4, Table 5 , Table 6 and Table 7 in the Appendix of Sun et al. (2011).

[9]Because of page limited, we did not report them here. The estimation results of k_l and ξ_l of industrial productivity distributions in each industry l using Pooled OLS, FE, LP and OP, respectively can be found in Table 8, Table 9, Table 10 and Table 11 in the Appendix of Sun et al. (2011).

[10]We use 4 approaches to estimate firm-level TFP in order to provide robust and consistent results in which has been treated separately or individually. The common features of the 4 methods all indicate similar distribution patterns, both in terms of distribution intensity and skewness, etc. The key feature of this paper is not to focus on econometric comparisons. However, we compare them econometrically for some industries. Interested readers can ask for the comparison report from the authors.

[11]According to our econometric comparison of results from these 4 approaches, all four estimations have skewness values less than 0, indicating negative skewness in productivity distribution. The Pooled OLS estimation has the highest skewness, , and the followings are LP, OP and FE. The Pooled OLS estimation has large proportion on the left side of the modal number, which is less reliable than the others. Moreover, the highest kurtosis value among four estimations is the Pooled OLS estimation, which indicating the steepest distribution among most four distributions.

[12]See Table 12 and 13 in the Appendix in Sun et al. (2011) for these results.

[13] di Giovanni et al. (2011) explains this difference by firms' heterogeneous fixed exporting costs.

[14]The paper does not consider Chinese processing trade firms. It's very difficult to predict the result because we are lack of information to identify which firm is a processing trade firm. However, we can guess the possible result by the size distributions of foreign-owned and non-foreign-owned firms. We find that they are very similar using kdensity estimating method for the Chinese firm-level data in 2007. This implies that our basic results given in this paper may not change much even if we take the processing trade firms out of the dataset.

[15]This may hold in China because firms of different ownership types are heterogeneously limited in exporting.

Appendix

year	Statistic checked observations	Having Investment	Having Middle Input	Having both I & M
1998	132821	42366	132747	42336
1999	142306	41910	142292	41906
2000	144537	38737	144332	38680
2001	152468	35408	152310	35353
2002	163965	34731	163627	34689
2003	183043	34086	183041	34086
2004	216954	36134	216757	36046
2005	257031	37308	256838	37276
2006	286607	38727	286594	38722
2007	321323	68867	321320	68866
total	2,001,055	408,274	1,999,858	**407,960**

Table 1: **Annual samples with/without investments and middle inputs**

Variable		Mean	Std. Dev.	Min	Max	Observations
ln Gross output	overall	8.832185	1.441823	3.680545	12.57972	N = 407919
	between		1.369184	3.705238	12.57972	n = 169902
	within		0.525238	3.076698	13.06407	T-bar = 2.40091
ln Value added	overall	7.445797	1.605989	-1.53839	13.27764	N = 407919
	between		1.493401	-1.39463	13.0022	n = 169902
	within		0.752093	-2.15765	13.01779	T-bar = 2.40091
ln Fix Capital	overall	7.828995	1.703263	-1.53839	14.79171	N = 407919
	between		1.692843	-1.53839	14.41346	n = 169902
	within		0.38811	0.041412	13.49087	T-bar = 2.40091
ln Labor	overall	5.391555	1.180301	2.302585	10.85476	N = 407919
	between		1.138575	2.302585	10.64044	n = 169902
	within		0.278806	0.860467	9.001826	T-bar = 2.40091
ln Middle Input	overall	8.601295	1.454204	-1.53839	13.99317	N = 407919
	between		1.405637	-1.53839	13.99317	n = 169902
	within		0.42944	-1.59255	14.07048	T-bar = 2.40091
ln Export	overall	7.964292	1.865408	-2.08778	13.82362	N = 107833
	between		1.853804	-1.70771	13.04174	n = 48133
	within		0.617398	1.169317	13.31133	T-bar = 2.24031
ln Investment	overall	5.115276	2.613863	-1.53839	15.19863	N = 407919
	between		2.444346	-1.53839	15.19863	n = 169902
	within		0.942194	-4.77117	14.45088	T-bar = 2.40091

Table 2: **Descriptive statistics of firms' basic financial variables**

	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
ζ_l	0.497	0.408	0.346	0.123	0.137	0.128	0.110	0.213	0.146	0.138	0.128	0.180	0.185	0.179	0.177	0.176	0.174	0.173	0.180	0.176
$\zeta_l > 0$	(0.013)	(0.012)	(0.015)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\zeta_l < 1$	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
χ_l	2.398	1.793	1.369	0.254	0.011	0.051	0.187	0.716	0.337	0.276	0.200	0.513	0.644	0.623	0.603	0.594	0.578	0.574	0.628	0.596
	(0.090)	(0.090)	(0.112)	(0.051)	(0.047)	(0.043)	(0.042)	(0.021)	(0.020)	(0.019)	(0.019)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
ψ_l	3.666	2.912	2.326	0.278	0.006	0.123	0.024	0.964	0.064	0.056	0.003	0.563	0.537	0.493	0.475	0.467	0.449	0.445	0.500	0.470
	(0.121)	(0.120)	(0.134)	(0.074)	(0.074)	(0.067)	(0.066)	(0.022)	(0.027)	(0.027)	(0.026)	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
R^2	0.775	0.704	0.496	0.371	0.326	0.331	0.307	0.506	0.380	0.368	0.346	0.357	0.397	0.400	0.394	0.393	0.388	0.387	0.401	0.394
	26	27	28	29	30	31	32	33	34	35	36	37	39	40	41	42	43	44	45	46
ζ_l	0.160	0.160	0.161	0.162	0.166	0.151	0.140	0.146	0.166	0.158	0.150	0.144	0.143	0.147	0.149	0.149	0.148	0.147	0.146	0.147
$\zeta_l > 0$	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\zeta_l < 1$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
χ_l	0.396	0.430	0.433	0.444	0.453	0.303	0.211	0.257	0.435	0.509	0.481	0.441	0.429	0.473	0.488	0.485	0.483	0.470	0.465	0.471
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
ψ_l	0.594	0.602	0.610	0.620	0.652	0.543	0.457	0.504	0.577	0.455	0.355	0.308	0.298	0.330	0.352	0.352	0.348	0.339	0.337	0.342
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
R^2	0.372	0.390	0.397	0.399	0.408	0.358	0.330	0.345	0.397	0.392	0.385	0.381	0.390	0.391	0.404	0.403	0.399	0.396	0.394	0.396

Table 3: **Estimation results of Pareto distributions of non-exporters' domestic sales and exporters' foreign sales based on productivity estimated using FE**