An Assessment of the Firm Level Impacts of Innovation, Export, Productivity Catch-up and Wages on Employment Growth in Chinese Manufacturing*

By

Jacques Mairesse[1] and Yilin Wu[2],

Abstract

This paper presents empirical evidence on the impacts of a number of important factors on employment growth at the firm level for a very large and representative panel data sample of Chinese manufacturing firms for the eight year period 1999-2006; it also explore how these impacts may vary across regions and industries, ownerships types and firm size classes. The analysis extends a previous one mainly focusing on the impact of innovation on employment for the same sample, which was directly based on the regression model proposed by Harrison, Jaumandreu, Mairesse and Peters (HJMP, 2008) and allowed a comparison of their results for France, Germany, Spain and the United Kingdom with the corresponding ones found for China (see Mairesse, Wu, Zhao and Zhen, 2012). The present study considers other important factors allowing us to decompose overall employment growth in several components respectively associated with the output growth of unchanged and innovating ("old" and "new") products for domestic demand and for export demand, with average productivity growth and wage growth, investment in fixed assets and catch-up to industry national or regional productivity frontier. The resulting picture is one of a complex pattern of effects, in which demand for old products and for domestic markets mainly, but also for new products and export markets, overcompensate the displacement effects related mostly to catch up productivity progress and to a lesser extent to wage increases.

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1 INSEE-CREST (France), UNU-MERIT (Maastricht University, Netherlands) and NBER (USA). Corresponding address: mairesse@ensae.fr.
2 Renmin University of China (Beijing, China), Corresponding address: wyl@nsrcruc.org.

1. Introduction

1.1 Main issues

Innovation is widely considered to be a primary source of macroeconomic growth and is of paramount importance for firm competitiveness and productivity. In China, like in most developed as well as developing countries, policies to encourage firm-level innovation are high on the economic agenda. Therefore, the impacts of innovation on employment are also of great concern and interest. However, the relationship between innovation and employment is particularly complex and difficult to ascertain and assess, and innovation itself has many facets with potentially contrasted effects. On the one hand, the long-run economic impact of innovation on employment is clearly not a negative one. For many decades, and even centuries, the improvement of innovation in advanced economies have been accompanied by employment growth instead of the ever-decreasing levels of jobs that many predicted. On the other hand, although the evidence suggests that innovative firms are more likely to survive and grow than firms that do not innovate, our understanding of the impacts of innovation on employment at the firm level remains rather vague. Process and organizational innovation contribute to productivity growth which leads to the result of reducing jobs, but product innovation stimulate demand, both domestic and foreign, for firms' products. Overall it is unclear to what extent and through what mechanisms employment is affected.

Export is also a very important factor of employment both by contributing to demand and motivating competitiveness and innovation. In China as in most countries, policies to encourage export are no less important policies to stimulate innovation. The effects of export on overall employment similarly to innovation remain unclear. Both for example may need for high quality workers, which will substitute to low skill workers. Like As the cost of employment, wage is also a factor that may bring displacement effect.

Productivity enhancements, whatever their causes and sources, due in particular to efforts to catch-up with the more efficient and cost effective firms constituting the "industry productivity frontier", contribute to the destruction and/or displacements of jobs, for a given levels of firms' outputs may be partly or over compensated by domestic and/or demand increases for firms' old, unchanged, improved and/or new products. Higher wages may have similar effects by incentivizing firms to make labor productivity efforts and/or invest in capital equipment which may substitute to labor.

1.2 Bird eye view of empirical literature on innovation and employment

The debate about the impacts of innovation and technological change on employment is a very old one (Jean-Baptiste Say, 1803; 1964 edition). It is still a relevant one, particularly for a rapidly developing country like China. Disentangling displacement and compensation effects of innovation raise many open questions both from theoretical and empirical points of view. Some scholars argue that innovation contribute mainly to productivity growth resulting overall in diminishing employment (Spiezia and Vivarelli, 2002). Others mainly stress that innovation and productivity growth stimulate demand, both domestic and foreign, thus promoting increasing employment. Our study provides a detailed picture of several of the various effects at work at the firm level, and tends to conclude that while product innovation has a positive impact on employment, process and organizational innovations (as reflected in productivity catching up effects) have important negative impacts.

Many recent studies, due to data availability, have provided evidence he positive effect of product innovation on employment growth. Using cross-sectional data for Germany, Zimmermann (1991) finds that technological progress in new product was responsible for the fall of employment during the 1980s, while Entorf and Pohlmeier (1990) find no significant effects. Brouwer et al. (1993) use two innovation surveys for the Netherlands to estimate the effects of innovation on employment growth rates.

They find a negative effect for overall R&D investments, but a positive effect for product-related R&D. Greenan and Guellec (2000), combining firm-level panel data with innovation surveys, observe that innovating firms (indicated by positive product innovation) have created more jobs than non-innovating ones. Piva and Vivarelli (2005), build a balanced panel of 575 Italian Manufacturing firms based on different surveys by Mediocredito-Capitalia for the period 1992-1997, and estimate a small but significantly positive relation between innovative investment on new product and employment.

While there is a widespread consensus in the literature on the positive impact of product innovation on employment at the firm-level, the evidence about process innovation is less clear-cut. Using the Community Innovation Survey (CIS) data for Germany, Peters (2004) finds a significantly positive impact of product innovation on employment, and a negative one for process innovation. In contrast, Blechinger et al. (1998) support the evidence of a positive relationship between process innovation and employment growth in the Netherlands and in Germany. Blanchflower and Burgess (1998) and Doms et al. (1995) find positive impacts of process innovation on employment growth, respectively in Australia and the U.K., and in the U.S. Recently, the paper by Harrison et al. (2005) uses CIS3 data (1998-2000) for France, Germany, U.K., and Spain found that although process innovation displaces employment, compensation effects from product innovation dominate in the four countries, albeit with some differences between them.

Recent studies that use the Community Innovation Survey (CIS)–the harmonized European innovation survey–also find out the positive relationship between of organizational innovation and employment growth rates. With this survey, comparable innovation data for different countries are available. Jaumandreu (2003) develops a specific model for the analysis of CIS data. Using Spanish CIS3 data of the year 2001 he finds that organizational innovation are responsible for net employment displacement and that product innovations and lead to a positive employment growth. Harrison et al. (2008) compare CIS3 data for France, Germany, Spain and the UK. Overall, the effects in the countries are quite similar. The same model has also been estimated by Hall-Lotti-Mairesse (HLM, 2008) for the Manufacturing sector in Italy over the period 1995-2003. The results show again positive effects of product innovation and organizational innovation on employment growth and demonstrate that displacement and compensation effects of process innovation are present in the manufacturing sector. Peters (2008) employs this model for Germany, extending the research to the service sector. For both the manufacturing sector and the service sector, she finds positive effects of organizational innovation.

Summarizing the results of this large set of firm-level studies, most of them have found positive effects of product innovation and organizational innovation on employment, but mixed evidence for process innovation. The total impacts of the different forms of innovation appear to be generally positive at the firm level in the U.S., Australia, and in most of the developed European countries. Still, a better assessment of such effects and mechanisms is particularly important for a well-informed implementation of innovation policy in China which has “a large pool of underemployed workers or workers in the informal sector” (Nannan Lundin and al. 2006, 2007; He Ping and al. 2008) and which faces the formidable challenge of a rapid and sustainable development in the present and coming years.

1.3 Present contribution

Our paper focuses precisely on the comparative assessment of the effects of product innovation and export on labor growth across the Chinese regions in all manufacturing industries, which includes industries more labor intensive and low-tech and export a lot, as well as industries more capital intensive, high-tech and also export oriented. The whole manufacturing industry is not only important on the Chinese domestic market but also on the world market. It has grown extremely fast and has been quite innovative in recent years for China as a whole, with inevitable wide differences across provinces and regions.[3] Our analysis thus rely on firm samples

[3] The differences across sub-industries and across type of firm ownerships are also important;

from the 1999-2006, which have been constructed from the yearly survey of industrial firms organized by China National Bureau of Statistics.

Our analysis extends substantively the simple framework pioneered by Harrison-Jaumandreu-Mairesse-Peters (HJMP, 2008) and the regression models estimated for the Manufacturing and the Service sectors in France, Germany, Spain and the United Kingdom (over the period 1998-2000). The same model has also been estimated by Hall-Lotti-Mairesse (HLM, 2008) for the Manufacturing sector in Italy (over the period 1995-2003).[4] This model builds up the relationship between the overall growth of employment at the firm level to the growth of firm output separately due to new (i.e., innovative) products and to old (i.e., unchanged) products. The possibility of separate measurement of output growth for new and old products follows directly from the firms' answers to the question on the new product output in a given year corresponds to new or substantially improved products introduced in this year and the two preceding years. This model can be also rewritten and viewed as a productivity regression assessing the impact of innovation on overall productivity growth. Although the two interpretations in terms of growth of labor and growth of productivity are exactly equivalent, we shall give preference here to the first one in the presentation and comments of our results.[5]As an extension to this model, we try to estimate the effect of old and new products separating them in to domestic old and new product and correspondingly export old and new products in order to figure out the effect of export in a symmetrical position. As we will see our present study although it largely concurs with previous findings, provides a more detailed and nuanced picture of a larger variety of effects at work at the firm level. It tends to conclude that in China, while product innovation has a positive impact on employment, process and organizational innovations (as reflected in productivity catching up effects) have important negative impacts, but that overall demand effects

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we control for them in the econometric analysis, but we will not focus on them here.

4 It has also been estimated by Benavente and Lauterbach for Manufacturing in Chili (over the years 1998-2001). The results in this analysis are, however, very different from those found here and in the other two studies.

5 See HLM, 2008, for a presentation of the two sides of the results.

predominate, at least as long as economic growth remains very strong.

In the version of the regression model we consider here, the growth rate of labor is the dependent variable and the growth rates of the four kinds of products, the growth rate of wage per capita, fixed assets and also the distance to the industry productivity frontier and its growth are the basic explanatory variables. In HJMP, 2008, and HLM, 2008, the authors also include in the model as a possibly important explanatory variable a binary indicator for process innovation. Such a variable was not available in our data, but we think that our distance to the industry productivity frontier catch up variable is likely to encompass both process and organizational innovations.

On the basis of this model we also decompose the overall employment growth in nine components: respectively associated with the output growth of domestic old and new products; with the output growth of export old and new products; with the average productivity growth; with the average growth of wage per capita; with the average fixed assets growth; with the lag distance to the frontier; and with the growth of the frontier. The basic results are not so different from those that found in manufacture industry as a whole in France, Germany, Spain and the United Kingdom as well as those found in manufacture industries in Italy. They show that displacement effects stemming from distance to the frontier is large, and also the displacement of wage growth is quite large, but accompanied by the productivity growth, the effects related to product innovations and export are strong enough in general to compensate these displacement effects and improve employment to some extent. Nonetheless there are interesting differences in the results for the comparison across ownerships, regions, industries and scales in China.

The rest of this paper is organized as follows. Section 2 presents a brief explanation of regression model we considered to identify the effect of innovation activities on employment, with its specification and estimation and also our extension on it to export activities. In Section 3, we will present our data, the cleaning procedure and comment in some detail on the main descriptive statistics on employment, output and productivity growth, share of innovative output and export value. Section 4 discusses the estimate results we obtained for the impact parameter of product innovation and export on employment growth. In section 5, we will discuss the decomposition results of overall employment growth associated with output growth in the four kinds of products, productivity trend and wage trend. We also make a comparison between the decomposition of different ownerships, industries, regions and scales to see how this mechanism works in different groups of firms. Section 6 is a brief conclusion by summarizing the main results and sketching different perspectives and the data requirements for possibly extending and improving the analysis, and overcoming some of its main limitations.

2. Impact of Product Innovation on Employment

2.1 Theoretical framework

The output of a firm in a certain year can be divided into 2 kinds of goods: the old (unchanged) products, and the new products, which can be donated with i=1 and i=2, respectively. If observing firms in two different years, which can be denoted with t=1 and t=2, outputs of products in year t are denoted by Y_{1t} and Y_{2t}, respectively. We suppose year t=1 is the basic year and all products are old products which means Y_{21} is always equal to zero.[6] In year t=2, Y_{22} may also equals to zero if the firm does not introduce any new products between the two years.

The firm's production function can be written for a product of type i in year t as equation (1) if we assume that, firstly, the production functions for old and new products are separable with both having constant returns to scale in capital, labor and intermediate inputs. And secondly, the productions of old and new products are

[6] Comparing with former year(s), firms may have already introduce new products in year t=1. It has no effect in our model, but should be kept in mind in our estimation.

identical which allows higher or lower efficiency between them.

$$Y_{it} = \theta_{it} F(K_{it}, L_{it}, M_{it}), \quad \text{i=1,2; t=1,2} \tag{1}$$

where θ represents efficiency, K, L and M stand for capital, labor and materials, respectively. In order to get a simple relation between the employment growth and output, we pay much attention to Y and L in the following equations. Assuming cost minimization, we can write the firm's cost function as the following:

$$C(w_{1t}, w_{2t}, Y_{1t}, Y_{2t}, \theta_{1t}, \theta_{2t}) = c(w_{1t})\frac{Y_{1t}}{\theta_{1t}} + c(w_{2t})\frac{Y_{2t}}{\theta_{2t}} + F \tag{2}$$

where the marginal cost *c(w)* is a function of the factors price vector *w*, and *F* represents fixed costs. According to Shephard's Lemma, we also have:

$$L_{it} = c_L(w_{it})\frac{Y_{it}}{\theta_{it}} \tag{3}$$

where $c_L(w_{it})$ represents the derivative of the marginal cost with respect to the wage.

Then, the employment growth can be divided into two terms in equation (4): the first $\frac{L_{22}}{L_{11}}$ part, $\frac{L_{12} - L_{11}}{L_{11}}$, is the employment growth for old products producer and the last part, , is the growth from new products producer.

$$\frac{\Delta L}{L} = \frac{L_{12} + L_{22} - L_{11}}{L_{11}} = \frac{L_{12} - L_{11}}{L_{11}} + \frac{L_{22}}{L_{11}} \tag{4}$$

We introduce equation (3) into equation (4), and then we get equation (5).

$$\frac{\Delta L}{L}=\frac{c_L(w_{12})Y_{12}/\theta_{12}-c_L(w_{11})Y_{11}/\theta_{11}}{c_L(w_{11})Y_{11}/\theta_{11}}+\frac{c_L(w_{22})Y_{22}/\theta_{22}}{c_L(w_{11})Y_{11}/\theta_{11}} \tag{5}$$

Assuming that the relative prices of inputs remain roughly constant in the two years and equal for old and new products, which means $c_L(w_{11}) = c_L(w_{12}) = c_L(w_{21}) = c_L(w_{22})$ we can understand the employment growth as the following approximate equation:

$$\frac{\Delta L}{L}\cong-\left(\frac{\theta_{12}-\theta_{11}}{\theta_{11}}\right)+\left(\frac{Y_{12}-Y_{11}}{Y_{11}}\right)+\frac{\theta_{11}}{\theta_{22}}\cdot\frac{Y_{22}}{Y_{11}} \tag{6}$$

Till now, the employment growth is divided into three components: the first is the change in efficiency in the production process for the old products, the second is the growth of old products output, and the third is the labor increase from expansion in production due to the introduction of new products or the effect of product innovation on employment growth. This effect depends on the relative efficiency θ_{11}/θ_{22} of old and new products. If new products are more efficient than old ones, the ratio is less than unity, and employment does not grow at the same pace as the output growth accounted for by new products.

2.2 Extended econometric model

We can simple replace the theoretical model above by using the numbers of domestic and export products to find out the effect of export only. But that is not our goal. We aim at interpreting the cross effect of these two important factors at the same time including the effect of wage growth, fixed asset growth, distance to frontier and its growth.

Following the model above, we use the following regression equations to estimate the parameters:

$$gl = \alpha_0 + \beta_1 y_1 + \beta_2 y_2 + \beta_0 others + u \tag{7}$$

where l is the growth rate of employment between year t=1 and t=2, y_1 is the contribution of old products to output growth which equals to $\frac{Y_{12} - Y_{11}}{Y_{11}}$, by introducing the information of domestic and export goods, it can be decomposes to $\frac{Y_{12d} - Y_{11d}}{Y_{11}} + \frac{Y_{12e} - Y_{11e}}{Y_{11}}$; y_2 is the contribution of new products to output growth which equals to $\frac{Y_{22}}{Y_{11}}$, it can also be decomposes to $\frac{Y_{22d}}{Y_{11}} + \frac{Y_{22e}}{Y_{11}}$; and u is a random disturbance which has a mean of zero. For the parameters, α_0 is the constant of the model; β_0 is the effect coefficient of other independent variables which we will interpret below; β_1 is the marginal cost in efficiency units of producing old products, which will be constraint to 1 in order to get a relative level of new product effects. β_2 is the marginal cost in efficiency units of producing new products, comparing with old products. It can help us to identify the gross effect of product innovation on employment.

To be more specific, the model will be rewritten as the following equations (8) or (9) that are in fact equivalent.

$$\begin{aligned} gl_{it} &= \alpha_0 + \beta_{do} wgqdo_{it} + \beta_{eo} wgqeo_{it} + \beta_{dn} ngqdn_{it} + \beta_{en} ngqen_{it} \\ &\quad + \sum_{k=1}^{K} \delta_k \operatorname{var}(k)_{it} + \sum_{j=1}^{J} \alpha_{0j} dum(j)_{it} + \varepsilon_{it} \\ &\text{and} \quad \beta_{do} + \beta_{eo} = 1 \end{aligned} \tag{8}$$

$$
\begin{aligned}
gl_{it} &= \alpha_0 + gq_{it} + \gamma_{do} wgqdo_{it} + \gamma_{eo} wgqeo_{it} + \gamma_{dn} ngqdn_{it} + \gamma_{en} ngqen_{it} \\
&\quad + \sum_{k=1}^{K} \delta_k \operatorname{var}(k)_{it} + \sum_{j=1}^{J} \alpha_{0j} dum(j)_{it} + \varepsilon_{it} \\
&\text{with} \quad \gamma_{do} = \beta_{do} - 1,\ \gamma_{eo} = \beta_{eo} - 1, \\
&\qquad\quad\ \ \gamma_{dn} = \beta_{dn} - 1,\ \gamma_{en} = \beta_{en} - 1, \\
&\text{and} \quad \gamma_{do} + \gamma_{eo} = -1
\end{aligned} \tag{9}
$$

In both the regression equations (8) and (9) gl and gq are the usual growth rates of firm employment and output between year t=1 and t=2; and the four "weighted" growth rates of products are defined by the following formulas:

$$
\begin{aligned}
& gq = (q - l.q)/l.q = wgqdo + wgqeo + ngqdn + ngqen \\
& \text{with } wgqdo = (qdo - l.qd)/l.q = \frac{(qdo - l.qd)}{l.qd} \times \frac{l.qd}{l.q} \\
& \qquad wgqeo = (qeo - l.qe)/l.q = \frac{(qeo - l.qe)}{l.qe} \times \frac{l.qe}{l.q} \\
& \qquad ngqdn = qdn/l.q \\
& \qquad ngqen = qen/l.q
\end{aligned}
$$

where $wgqdo$ and $wgqeo$ stand for the weighted growth rate of domestic old product and export old product (equal to the usual growth rates of domestic old product and export old product weighted by their proportion in the previous year), and where, as explained above, $ngqdn$ and $ngqen$ can be viewed as generalized weighted growth rates of domestic new product and export new product between year t-1 when they do not exist (i.e., equal to zeros) and year t.

The other variables noted $\sum_{k=1}^{K} \delta_k \operatorname{var}(k)_{it}$ in regression equations (8) and (9) are the growth rate of the average wage per employee grw, the growth rate of beginning of year fixed assets gfa, the distance to industry productivity frontier in the period t-2 dis, the corresponding growth rate of this frontier gfr. More precisely, the frontier is defined as the p95 percentile of productivity within 29 industries (2-digit level) and five large regions, with productivity measured as:

$$Prod_{it} = \ln(\text{Gross Output / Number of Employees})$$
$$Dis_{it}^{ind,\,reg} = p95 \text{ of } Prod_{it}^{ind,\,reg} - Prod_{it}$$
$$Gfr_{t}^{ind,\,reg} = p95 \text{ of } Prod_{t}^{ind,\,reg} - p95 \text{ of } Prod_{t-1}^{ind,\,reg}$$

Finally, note also that $\alpha_0 = \sum_{j=1}^{J} \alpha_{0j} dum(j)_{it}$ stands for stand for four groups of dummies, reg_j, ind_q own_k, and sca_m., corresponding respectively to five large, four industries, three firm ownership types and three size groups.

These four groups of dummy variables are precisely defined as follows. Region dummies correspond to the five main regions of China themselves defined on the basis of the 31 mainland provinces: Bohai Rim region, Yangtze River Delta, Pearl River Delta, Middle China and West China.[7] Industries dummies are specified according to the OECD industry classification of High-tech, medium-high-tech, medium-low-tech, and low-tech industries, and defined on the basis the 29 manufacturing industries (2 digit-level). Ownership dummies are constructed on the basis of the 7 registration types of firms in 7 groups, as well information on capital shares, which are recorded in the in the Chinese Industrial yearly Census. We thus distinguish state owned, private and foreign firms (including Hong-Kong and Macao owned firms). Finally, size dummies are defined on the basis of the numbers of employees, with large firms having more than 2000 employees; medium firms between 300 to 2000 employees, and small firms less than 300 employees.

[7] The division of provinces follows the standard of the China National Bureau of Statistics and the attribution of each province is the following: Bohai Rim region includes Beijing, Tianjin, Hebei, Liaoning and Shandong; Yangtze River Delta includes Shanghai, Jiangsu and Zhejiang; Pearl River Delta includes Fujian, Guangdong, Guangxi and Hainan; Middle China includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan; West China includes Chongqing, Sichuan, Yunnan, Guizhou, Tibet, Shaanxi, Ningxia, Qinghai, Gansu and Xinjiang.

3. Data

3.1 Data source and sample cleaning and construction

The basic source of our data comes from the yearly industrial surveys organized by China National Bureau of Statistics, which cover all state-owned firms and non-state-owned firms with sales higher than 5 million RMB Yuan. Since the panel data sample that can be constructed from these surveys is very large, and because we specify our econometric equations in terms of first differences of variables and choose to lag some of them to avoid possible simultaneity biases and/or to rely on others to be used as instrument variables, we have only kept firms with non-missing observations for our main variables and present for at least over at least four consecutive years. Although it is an unbalanced panel over our eight year study period, it can thus be seen as the reunion of five overlapping balanced subsamples respectively for the 1999- 2002, 2000-2003, 2001-2004, 2002-2005 and 2003-2006 sub-periods.

Table 1 gives the numbers of firms for each of these five balanced panel data sub-samples after proper cleaning for missing observations and/or outliers. We document in detail these various cleaning procedures in Appendix 1. Overall we obtain an unbalanced sample of 406425observations over the eight years 1999-2006. However, since most of our regressions involve three lags, our study sample will actually be of 257371 observations (63%). It can also be for some IV estimations of only 182844 observations.

(Insert about here Table 1)

3.2 Descriptive Statistics

Descriptive statistics on our main variables for our study sample are presented in

Tables 2 to 4. We can see in in Table 2 that the average annual growth rate of employment is 4.1% in the 8 years, but it varies a lot among firms: more than 25% of firms have a negative employment growth rate while 25% have an annual growth rate of employment higher than 9%. We see also the growth of rate of output for domestic for old domestic products is by far fastest: with an annual growth average of about 10% as against 2-3% for old export and new domestic products and only 1% for new export products. There also the dispersion among firms is huge with about 25% of them with an annual growth rates for old domestic products respectively negative and less than -6.5% and positive and above 24%.

(Insert about here Table 2)

Table 3 complements the picture given by Table 2 by showing the relative shares and growth performances of four categories of firms that we can distinguish in the data: the firms that never or most often do not innovate in new products and do not export which constitute nearly 60% of our sample, those that do not innovate in new products and export only old products which amount to another 30%, and finally those reporting they innovate but do not export those reporting they both innovate and export, which are respectively about 4-5% and 5-6% of our sample. We see also that the average annual growth rates of employment and labor productivity of these four categories of firms differ significantly though not hugely. In Appendix 2 we explain how we precisely distinguish these four categories of firms and have been able in practice to decomposing total overall output in all products in four components, knowing only total export output and total new product output.

(Insert about here Table 3)

Table 4 gives us basic information about other model variables. We see in particular that the dispersion for all them is again extremely high in spite of our important cleaning for outliers. We can note also that defining the distance to the industry productivity frontier at the level of 2 digit industry or 3 digit industry classifications does not make significant difference in average but that the latter is much more dispersed than the first, as could be expected. We have tested that in fact that using one or the other in our regression does not significantly affect our estimation results.

(Insert about here Table 4)

4. Estimation results

We estimated systematically 7 different regressions ranging from the most simple ones imposing a priori that the estimated impacts of our demand variables would all constrained to be equal to 1 as a benchmark (regressionC1_1) to the ones including all our other variables (regression C1_7), that is in terms of equation (8) in the text (and the β coefficients of our first normalization):

C1_1 $\beta_{do} = \beta_{eo} = \beta_{dn} = \beta_{en} = 1$
C1_2 $\beta_{do} = \beta_{eo} = 1 \quad \beta_{dn} = \beta_{en} \neq 0$
C1_3 $\beta_{do} = \beta_{dn} \neq 0 \quad \beta_{eo} = \beta_{en} \neq 0$ and $\beta_{do} + \beta_{eo} = 1$
C1_4 $\beta_{do} \neq \beta_{eo} \neq \beta_{dn} \neq \beta_{en} \neq 0$ and $\beta_{do} + \beta_{eo} = 1$
C1_5 $\beta_{do} \neq \beta_{eo} \neq \beta_{dn} \neq \beta_{en} \neq 0$ and $\beta_{do} + \beta_{eo} = 1$ with grw and gfa
C1_6 $\beta_{do} \neq \beta_{eo} \neq \beta_{dn} \neq \beta_{en} \neq 0$ and $\beta_{do} + \beta_{eo} = 1$ with grw, gfa, dis and gfr calculate in two digit industry
C1_7 $\beta_{do} \neq \beta_{eo} \neq \beta_{dn} \neq \beta_{en} \neq 0$ and $\beta_{do} + \beta_{eo} = 1$ with grw, gfa, dis and gfr calculate in three digit industry

We have estimated these regressions with both types of normalization, that is also as equation (9) in terms of the coefficients. Since they are strictly equivalent, we show here in Table 5 below our results for our more intuitive first normalization, and document those for the second normalization in the first Table of Appendix 3.

(Insert about here Table 5)

Looking at the different estimates of product demand elasticities and other employment determinant across the seven specifications in Table 5, we can see that they are all statistically very significant which is not surprising with regard to the very large size of our sample. But we can see that most seem also to make economic sense, which will be more evident when we consider what they mean in terms of the employment growth decomposition we present now in Section 5.

5. Employment Growth Decomposition Based on the Extended Model

5.1 Employment Growth Decomposition

Using the estimated coefficients of specification C1_6 , in fact not different from C1_7, the employment growth rate can be written in terms of the following four components:

$$gl = \left\{ \begin{array}{c} I(wgrqdo > 0)\hat{\beta}_{do} wgrqdo + I(wgrqeo > 0)\hat{\beta}_{eo} wgrqeo \\ +I(ngrqdn > 0)\hat{\beta}_{dn} ngrqdn + I(ngrqen > 0)\hat{\beta}_{en} ngrqen \\ \hat{\delta}_1 grw + \hat{\delta}_2 gfa + \hat{\delta}_3 dis + \hat{\delta}_4 gfr \\ \hat{\alpha}_0 \\ \sum_j \hat{\alpha}_{0j} reg_j + \sum_k \hat{\alpha}_{0k} own_k + \sum_l \hat{\alpha}_{0l} ind_l + \sum_m \hat{\alpha}_{0m} sca_m + \sum_p \hat{\alpha}_{0p} per_p \end{array} \right\}$$

The first component explains the employment change caused by output growth of these four kinds of product growth.

$$\begin{array}{c} I(wgrqdo > 0)\hat{\beta}_{do} wgrqdo + I(wgrqeo > 0)\hat{\beta}_{eo} wgrqeo \\ +I(ngrqdn > 0)\hat{\beta}_{dn} ngrqdn + I(ngrqen > 0)\hat{\beta}_{en} ngrqen \end{array}$$

The second component ($\hat{\delta}_1 grw + \hat{\delta}_2 gfa + \hat{\delta}_3 dis + \hat{\delta}_4 gfr$) describes the employment change associated with wage growth, fixed assets growth, and distance to the frontier.

The third component ($\hat{\alpha}_0$) is the average level of productivity trend, while the fourth ($\sum_j \hat{\alpha}_{0j} reg_j, \sum_k \hat{\alpha}_{0k} own_k, \sum_l \hat{\alpha}_{0l} ind_l, \sum_m \hat{\alpha}_{0m} sca_m, \sum_p \hat{\alpha}_{0p} per_p b$) measures the difference of employment growth in different regions and industry, and by types of ownership and classes of firm size.

We can calculate each component in firm level and summarize them by firms within the same character, e.g. firms have the same kind of ownership, in the same region, in the same technology level or in the same size, so that we can compare the difference of components by ownership, region, sector and size in an average level.

Chart 1: Employment Growth Decomposition base on Model C1_6 (2 digit industry)

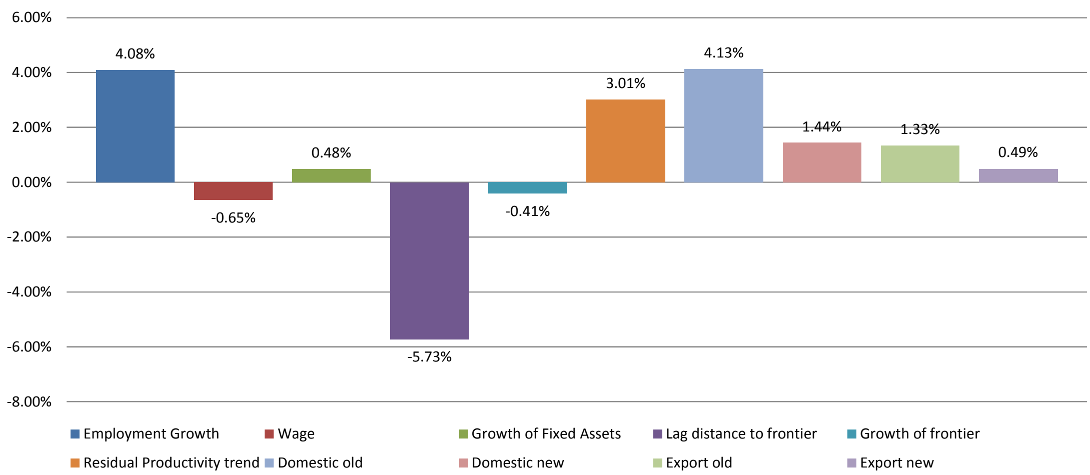

Chart 1 shows us the decomposition result of the full model. We can see that the 4.08% growth of employment is driven by several factors. First we can see that a displacement effect of wage growth of -0.65%. And a miner effect of fixed asset growth is detect while a really large effect of displacement from technology growth is following showing the repaid growth of technology level of Chinese Firms. But we are happy to find that all this large displacement effect is compensated by the product procedure. The product growth itself contributes 3.01%, while domestic old product plays an important role of 4.13%, and although taking relatively small amount of product proportion, we still see the positive effect of innovation and export to employment growth in China.

5.2 Employment growth decomposition by ownership type

(Insert about here Table 6)

From the description data of Table 6 we can see that, in our 8 years sample, State owned firms are the majority of Chinese manufacturing industry. But state owned firms suffered a small growth in employment in average, although they have the highest level of export old product proportion of 4.6%, the lowest level of new product proportion may be the cause of this low speed growth. By contrast, foreign firms have the highest growth of employment accompanied with highest level of export and modest innovation level.

The result of decomposition shows the trend that domestic old product play the main part of contribution to compensate the negative effect by productivity and wage growth, and state owned firms and private firms seems more relay on it. Also, innovation is relatively a main source of state owned firms' employment growth. Obviously, the high growth of employment of foreign firms is attributed to the export of their products.

5.3 Employment growth decomposition by region

In order to explore the difference of regions in China, we divide the 31 provinces in mainland China into five regions which are Bohai Rim, Yangtze River Delta, Pearl River Delta, Middle China and West China. From the results on the tables and graph, we can see the difference of component strength in each region.

From the descriptive statistics, we can see that Yangtze Delta and Pearl River Delta share the higher employment growth with the lowest productivity growth. But firms in Yangtze River Delta seems more rely on innovation with a modest export level while firms in Pearl River Delta relied more on export with relatively low innovation level. Another extreme is west China, which has the highest level of new product but suffers from diminishing employment. In that scene, it seems that in this period of China, export contribute more to labor demand and employment growth than innovation due to the reason that the effect of export comes more quickly and directly.

The trend of export oriented employment growth can also be seen in the decomposition graph. As the contribution of old and domestic products goes down and the contribution of export goes up, the growth rate of employment goes up. And innovation plays a conspicuous assistant role in the promotion of employment.

(Here insert Table 7)

5.4 Employment growth decomposition by industry technology level

(Here insert Table 8)

Base on the industry definition of High-tech, medium-high-tech, medium-low-tech, and low-tech industries from OECD, we also consider these four groups in the decomposition. It is obvious that there are least firms in high tech sectors, but they dominate in almost all the indicators with a lowest wage growth and productivity growth. That explains the role of displacement effect is important and should be taken into consideration. And on the opposite, the low tech sector, although with a high export proportion, still suffer a decrease in employment due to the fact that lacking of the help of innovation, low tech export cannot fulfill it is function in employment. This trend can also be seen in the graph that in this four groups of industries, the growth rate of employment decline as the impact of innovation becomes smaller.

5.5 Employment growth decomposition by size

(Here insert Table 9)

In the manufacturing industry of China, most of the firms are small firms (68.3%) and they have an averagely negative growth of employment, evidence from the description table supports that they have the highest wage growth as well as productivity growth, but relatively low level of innovation and export. The large firms, although only takes up 3.3% of the numbers of firms, have the highest employment growth with high innovation and export.

The decomposition graph also shows the difference structure of employment growth, on which large firms have a more diverse structure with effects from all the four kinds of products.

6 Conclusion

By using a simple equation developed in HJMP (2008) and HLM (2008), this paper analyses the impact of new product and export product output in improving employment growth in firm level, and the difference of relative components in improving it in several groups of firms in China.

The model and decomposition result shows that the growth of output for the domestic market plays a major role for employment growth (5.56%=4.13%+1.44%), about 3 times larger than for exports (1.82%=1.33%+0.49%).Innovation has a positive effect on employment growth, but a modest one: 1.92% (1.44% for the domestic market , 0.49% for export) The growth of wage has a significant negative effect (-0.65%) while growth of fixed assets has negligible effect. And catching up to the productivity frontier corresponding to process and organizational innovation has to the largest effect (-5.73%). As reflected in the residual productivity trend, it appears that the average employment growth could have been positive of about 1.07%(=4.08%-3.01%), and labor product lower by -1.07%.

The average level of output and growth of basic data shows that proportion of product innovation is not high in either low-tech sectors or high-tech sector, but the growth of output and productivity are quite fast in recent years. Fast growth of product innovation itself is a great promoter of employment in Chinese manufacturing firms. When this innovation interacts with growth of export as another motivation to product, the effect becomes even larger. But the high average specific trend in decomposition indicating the displacement effect of productivity and wage growth proves that China is still playing a role of manufacturing factory in world market. We also find that the growth of old products in exporters and non-exporters play an important role in compensating the effect of productivity growth and wage growth.

For further improvement, we will try to find out some good instruments to solve the endogeneity problem of our four growth output variables. The regression results of a first tentative attempt of finding the proper instrument variables are shown in Table 14. They show that imposing the constraints of constant returns to scale (wrqdo+wrqde=1) does much to mitigate the problem.

Tables

Table 1: Numbers of firms in different periods

Time Period	Numbers of firms
1999-2002	32318
2000-2003	31786
2001-2004	34050
2002-2005	38568
2003-2006	46122

Table 2：Descriptive statistics of main variables

%	Employment Growth	Old and domestic product growth	Old and export product growth	New and domestic product growth	New and export product growth
mean	4.1	9.8	2.5	3.4	1.0
sd	23.8	36.4	23.5	15.4	7.7
p5	-26.2	-40.1	-22.5	0.0	0.0
p25	-5.8	-6.5	0.0	0.0	0.0
p50	0.0	4.2	0.0	0.0	0.0
p75	9.2	24.1	0.0	0.0	0.0
p95	45.9	73.8	38.3	21.7	0.4

Table 3: Descriptive statistics of four types of firms

	Firms	Percentage (%)	Employment Growth (%)	Productivity Growth (%)	New Product (%)	Export (%)
none, none	150,493	58.47	3.0	15.3	0.0	0.0
NPV, none	11,590	4.5	3.1	16.0	37.7	0.0
none, EXP	80,818	31.4	6.2	12.5	0.0	62.8
NPV, EXP	14,470	5.62	4.5	16.0	35.3	35.1
Total	257,371	100	4.1	14.5	3.7	21.7

Table 4: Descriptive statistics of other model variables

stat s	Employees	Employees Growth (%)	Productivity Growth (%)	Wage Growth (%)	Fixed Assets	Fixed Assets Growth (%)	Distance to frontier (2d)	Frontier Growth (2d)	Distance to frontier (3d)	Frontier Growth (3d)
mean	435	4.1	14.5	18.2	57113	8.2	1.34	0.10	1.28	0.10
sd	1528	23.8	32.5	75.4	561752	21.5	0.80	0.14	0.79	0.24
p05	40	-26.2	-30.3	-35.4	699	-23.9	-0.01	-0.08	0.00	-0.24
p25	90	-5.8	-6.6	-6.5	2804	-3.4	0.82	0.04	0.76	0.00
p50	176	0.0	9.8	7.0	7492	5.4	1.37	0.10	1.29	0.11
p75	378	9.2	29.9	25.7	23526	19.1	1.88	0.16	1.80	0.21
p95	1440	45.9	76.4	91.7	155320	47.0	2.59	0.29	2.54	0.44

Table 5: Estimation Results of the extended Model

Model	C1_1	C1_2	C1_3	C1_4	C1_5	C1_6	C1_7
wgrqdo	1	1	0.426*** (0.001)	0.425*** (0.001)	0.421*** (0.001)	0.419*** (0.001)	0.420*** (0.001)
wgrqeo	1	1	0.574*** (0.001)	0.575*** (0.001)	0.579*** (0.001)	0.581*** (0.001)	0.580*** (0.001)
ngrqdn	1	0.879*** (0.003)	0.426*** (0.001)	0.405*** (0.003)	0.404*** (0.003)	0.389*** (0.003)	0.392*** (0.003)
ngrqen	1	0.879*** (0.003)	0.574*** (0.001)	0.506*** (0.006)	0.512*** (0.006)	0.507*** (0.006)	0.506*** (0.006)
grw					-0.035*** (0.001)	-0.036*** (0.001)	-0.036*** (0.001)
gfa					0.062*** (0.002)	0.050*** (0.002)	0.051*** (0.002)
dir(2-digit)						-0.043*** (0.001)	
gfr(2-digit)						-0.039*** (0.003)	
dir(3-digit)							-0.041*** (0.001)
gfr(3-digit)							-0.035*** (0.002)
dyr	√	√	√	√	√	√	√
reg	√	√	√	√	√	√	√
ind	√	√	√	√	√	√	√
own	√	√	√	√	√	√	√
sca	√	√	√	√	√	√	√
constant	-0.127*** (0.002)	-0.117*** (0.002)	-0.022*** (0.001)	-0.020*** (0.001)	-0.019*** (0.002)	0.045*** (0.002)	0.039*** (0.002)
Root MSE	0.345	0.344	0.238	0.238	0.226	0.223	0.223
Sample Size	331898	331898	331898	331898	265659	257371	257371

Table 6: Descriptive Statistics and Employment Growth Decomposition by Ownership

	Employment Growth (%)	Wage Growth (%)	Growth of Fixed Assets (%)	Lag distance to frontier (t-2)	Growth of frontier (%)	Domestic old (%)	Domestic new (%)	Export old (%)	Export new (%)	Residual Productivity trend (%)	Numbers of Obs. (%)
					Descriptive Statistics						
State Own	1.6	16.8	7.8	145.5	11.1	8.7	0.7	4.6	0.7	-	44.0
Private	5.7	19.1	13.1	137.8	11.2	14.7	2.6	2.5	0.9	-	28.5
Foreign	6.4	19.5	8.5	112.7	8.4	6.6	5.2	2.4	1.4	-	27.5
					Decomposition base on whole sample model						
State Own	1.6	-0.6	0.4	-6.2	-0.4	3.7	0.4	1.8	0.4	2.2	44.0
Private	5.7	-0.7	0.7	-5.9	-0.4	6.2	1.5	1.0	0.4	3.0	28.5
Foreign	6.4	-0.7	0.4	-4.8	-0.3	2.8	3.0	0.9	0.7	4.4	27.5

Table 7: Descriptive Statistics and Employment Growth Decomposition by Regions

	Employment Growth (%)	Wage Growth (%)	Growth of Fixed Assets (%)	Lag distance to frontier (t-2)	Growth of frontier (%)	Domestic old (%)	Domestic new (%)	Export old (%)	Export new (%)	Residual Productivity trend (%)	Numbers of Obs. (%)
					Descriptive Statistics						
Bohai Rim	2.9	21.5	8.5	143.3	13.4	11.8	1.9	3.9	0.8	-	18.6
Yangtze River Delta	4.9	14.7	11.5	130.3	8.7	8.9	2.8	3.5	1.3	-	41.4
Pearl River Delta	5.9	21.6	7.8	140.8	6.4	8.0	4.4	1.6	0.9	-	17.9
Middle China	2.3	19.9	7.9	131.6	15.0	12.5	1.0	3.7	0.4	-	13.7
West China	1.4	18.5	8.0	124.0	13.3	10.0	0.3	5.3	0.4	-	8.3
					Decomposition base on whole sample model						
Bohai Rim	2.9	-0.8	0.4	-6.1	-0.5	5.0	1.1	1.5	0.4	1.9	18.6
Yangtze River Delta	4.9	-0.5	0.6	-5.6	-0.3	3.7	1.7	1.4	0.7	3.4	41.4
Pearl River Delta	5.9	-0.8	0.4	-6.0	-0.2	3.3	2.6	0.6	0.5	5.6	17.9
Middle China	2.3	-0.7	0.4	-5.6	-0.6	5.2	0.6	1.4	0.2	1.3	13.7
West China	1.4	-0.7	0.4	-5.3	-0.5	4.2	0.2	2.0	0.2	0.8	8.3

Table 8: Descriptive Statistics and Employment Growth Decomposition by Industry technology level

	Employment Growth **(%)**	Wage Growth **(%)**	Growth of Fixed Assets **(%)**	Lag distance to frontier (t-2)	Growth of frontier **(%)**	Domestic old **(%)**	Domestic new **(%)**	Export old **(%)**	Export new **(%)**	Residual Productivity trend **(%)**	Numbers of Obs. **(%)**
					Descriptive Statistics						
High-tech	6.1	17.6	10.9	155.6	7.6	3.2	2.5	8.0	2.5	-	7.0
Medium-high-tech	4.5	17.8	10.8	137.7	11.7	10.8	1.9	5.6	1.1	-	32.2
Medium-low-tech	3.5	18.5	8.7	135.4	11.9	11.5	2.5	2.1	0.7	-	27.7
Low-tech	3.7	18.5	8.6	125.6	8.4	9.0	3.0	1.5	0.7	-	33.2
					Decomposition base on whole sample model						
High-tech	6.1	-0.6	0.5	-6.6	-0.3	1.4	1.5	3.1	1.3	5.9	7.0
Medium-high-tech	4.5	-0.6	0.5	-5.9	-0.5	4.5	1.1	2.2	0.5	2.6	32.2
Medium-low-tech	3.5	-0.7	0.4	-5.8	-0.5	4.8	1.5	0.8	0.4	2.5	27.7
Low-tech	3.7	-0.7	0.4	-5.4	-0.3	3.8	1.7	0.6	0.4	3.2	33.2

Table 9: Descriptive Statistics and Employment Growth Decomposition by Size

	Employment Growth **(%)**	Wage Growth **(%)**	Growth of Fixed Assets **(%)**	Lag distance to frontier (t-2)	Growth of frontier **(%)**	Domestic old **(%)**	Domestic new **(%)**	Export old **(%)**	Export new **(%)**	Residual Productivity trend **(%)**	Numbers of Obs. **(%)**
					Descriptive Statistics						
Large	6.9	17.7	12.5	125.5	11.2	3.3	2.3	11.1	3.0	-	3.3
Medium	6.2	16.5	10.7	146.9	10.1	7.4	3.4	5.2	1.6	-	28.4
Small	3.1	19.0	8.8	129.5	10.4	11.2	2.1	2.3	0.6	-	68.3
					Decomposition base on whole sample model						
Large	6.9	-0.6	0.6	-5.4	-0.4	1.4	1.3	4.3	1.5	4.2	3.3
Medium	6.2	-0.6	0.5	-6.3	-0.4	3.1	2.0	2.0	0.8	5.0	28.4
Small	3.1	-0.7	0.4	-5.5	-0.4	4.7	1.2	0.9	0.3	2.1	68.3

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Appendix 1: Cleaning procedures

For the original firm data, we deleted those firms with employees less than 10, sales revenue or gross output less than 5 million Yuan, and firms with negative wage or wage per capita less than 1 thousand Yuan. Then, the log growth rate of gross output, productivity, and wage per capita of each firm are calculated. Firms with all the three kinds of growth rates in-between -0.7 and 2 are kept. After that, we calculated the growth rate of labor, and kept the firms for which these rates did not appear extremely large (outside of the range from –0.7 to 1 in logs).

And we also do some adjustment to the data on the variables that we concerned about. For export value, replace it by 0 if it is less than 0, replace by its top level which is gross sale revenue if it is larger than gross sales revenue. For new product value, replace it by 0 if it is less than 0, replace by its top level which is gross output if it is larger than gross output. What is more we adjust the value of new product and export to extreme in firms with proportion of new product or export in gross output less than 1% or higher than 99%.

There is a flaw of our data set that in 2004, since a nation economic survey is conducted, so the new product value and R&D value are missing in this year. So we try to invent these values by simple average of the corresponding values in 2003 and 2005. And replace these values by 0 if the numbers of these indicators are also missing in the year 2003 or 2005.

Appendix 2: Decomposing total output in new products and in exported products in four components, respectively a domestic component and an export one, and an old product component and a new product one

As we have mentioned above, the second step of introducing export to our model is that we decompose the effect of export and innovation on product level instead of firm level distinction. The effect of export will be estimated with a more promising generalized specification in which the growth rate of output is decomposed not only into two components: the growth rates of "old" and "new" products, but into four components: the growth rates of "domestic-old", "domestic-new" , "export-old", and "export-new" products. Our framework considers a four-way product output distinction in domestic-old (do), domestic-new (dn), export-old (eo) and export-new (en).

For each firms, we use q to denote the gross output after the price adjustment. Then we have

$$q = q_o + q_n = q_d + q_e$$

in which qo means old product output after price adjustment, and qn, qd, qe means that of new product, domestic product and export product respectively. But in the survey we have only the two-way decomposition of total output in domestic and export output separately from that in old and new output. We have to "combine" these two different distinctions, and in practice we have to consider 9 different cases, which we can characterized by the four binary indicators bd, be, bo and bn of whether qdo, qdn , qeo and qen are positive or null.

Then we define a vector $S(b_d, b_e, b_o, b_n)$ construct by the dummies to indicate whether the firm has certain kinds of product or not. Since each firm at least have two kinds of products, there are 9 situation considered here.

Table 10: The nine different cases of innovation and export of the sample

S(bd，be，bo，bn)	qdo	qdn	qeo	qen	Numbers of firms	Proportion of firms
S(1，0，1，0)	q	0	0	0	150493	58.5
S(1，0，0，1)	0	q	0	0	867	0.3
S(0，1，1，0)	0	0	q	0	22670	8.8
S(0，1，0，1)	0	0	0	q	245	0.1
S(1，1，1，0)	qd	0	qe	0	58148	22.6
S(1，1，0，1)	0	qd	0	qe	660	0.3
S(1，0，1，1)	qo	qn	0	0	10723	4.2
S(0，1，1，1)	0	0	qo	qn	844	0.3
S(1，1，1，1)	?	?	?	?	12721	4.9
Total					257371	100

Since the S(1,1,1,1) is the most complicated situation and we do not have the exact numbers of product values of each kinds, so we have to make some assumptions. The problem is to find plausible solutions for the over-identified simultaneous equations, i.e. 4 equations of which 3 are independent for 4 unknowns

$$\begin{cases} qdo + qdn = qd \\ qdo + qeo = qo \\ qdn + qen = qn \\ qeo + qen = qe \end{cases}$$

An average solution is to base the imputation on an average proportion assumption, that is:

$$\begin{cases} qdo = (qd \bullet qo) / q \\ qdn = (qd \bullet qn) / q \\ qeo = (qe \bullet qo) / q \\ qen = (qe \bullet qn) / q \end{cases}$$

We can also consider two extreme solutions based on the following conditions which have to be satisfied by all possible solutions and which are summarized in the

Table below.

Table 11: The possible extremes of the equations

		$qe-qo=qn-qd=qe+qn-q$	
	Conditions	>=0	<0
$qe-qn$ $=qo-qd$ $=qe+qo-q$	>=0	（1）qdn=0 or （2）qdo=0	（1）qdn=0 or （2）qen=0
	<0	（1）qeo=0 or （2）qdo=0	（1）qeo=0 or （2）qen=0

The first extreme solution (1) is based on choosing a maximum value for qdo, i.e. qdn=0 in first row of Table, and qeo=0 in second row of the Table. Likewise the second extreme solution (2) is based on choosing a maximum value for qdn, i.e. qdo=0 in the first column of Table and qen=0 in the second column of the Table.

In order to be more objective on these assumptions, we also introduce a random binomial numbers to distribute them randomly into these two extremes. The proportion of each product under these four kinds of solutions are shown on table 4 below, since the difference only affect 10.14% of the firms, the result didn't show obvious bias between these four solutions.

Table 12: The comparison of the four possible solutions

%	*Domestic old*	*Domestic new*	*Export old*	*Export new*
Average proportion assumption	75.4	2.9	20.9	0.8
First extreme solution (qdn=0 or qeo=0)	75.8	2.5	20.5	1.1
Second extreme solution (qdo=0 or qen=0)	75.2	3.1	21.1	0.6
Random sampling of two extreme solutions	75.5	2.8	20.8	0.9

Appendix 3: Other estimation results

Appendix Table A3-1: Estimation results of the extended model in terms of alternative normalization, i.e. regression (9)

Model	C2_1	C2_2	C2_3	C2_4	C2_5	C2_6	C2_7
grq	1	1	1	1	1	1	1
wgrqdo			-0.574***	-0.575***	-0.579***	-0.581***	-0.580***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
wgrqeo			-0.426***	-0.425***	-0.421***	-0.419***	-0.420***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ngrqdn		-0.121***	-0.574***	-0.595***	-0.596***	-0.611***	-0.608***
		(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
ngrqen		-0.121***	-0.426***	-0.494***	-0.488***	-0.493***	-0.494***
		(0.003)	(0.001)	(0.006)	(0.006)	(0.006)	(0.006)
grw					-0.035***	-0.036***	-0.036***
					(0.001)	(0.001)	(0.001)
gfa					0.062***	0.050***	0.051***
					(0.002)	(0.002)	(0.002)
dir(2-digit)						-0.043***	
						(0.001)	
gfr(2-digit)						-0.039***	
						(0.003)	
dir(3-digit)							-0.041***
							(0.001)
gfr(3-digit)							-0.035***
							(0.002)
dyr	√	√	√	√	√	√	√
reg	√	√	√	√	√	√	√
ind	√	√	√	√	√	√	√
own	√	√	√	√	√	√	√
sca	√	√	√	√	√	√	√
constant	-0.127***	-0.117***	-0.022***	-0.021***	-0.019***	0.045***	0.039***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Root MSE	0.345	0.344	0.238	0.238	0.226	0.223	0.223
Sample Size	331898	331898	331898	331898	265659	257371	257371

Appendix Table A3-2: Comparing OLS and IV (still tentative) estimation results for the extended model

Model	OLS	IV	OLS	IV
Constraint	wrqdo+wrqde=1		No constraint	
wgrqdo	0.419***	0.558***	0.262***	0.616***
	(0.001)	(0.020)	(0.001)	(0.136)
wgrqeo	0.581***	0.442***	0.299***	0.766***
	(0.001)	(0.020)	(0.002)	(0.162)
grqdn	0.389***	0.309***	0.254***	0.487***
	(0.003)	(0.027)	(0.003)	(0.141)
grqen	0.507***	0.224***	0.291***	0.432**
	(0.006)	(0.057)	(0.006)	(0.173)
grw	-0.036***	-0.035***	-0.031***	-0.040***
	(0.001)	(0.002)	(0.001)	(0.004)
gfa	0.050***	0.044***	0.085***	0.010
	(0.002)	(0.003)	(0.002)	(0.026)
dis	-0.043***	-0.043***	-0.041***	-0.043***
	(0.001)	(0.001)	(0.001)	(0.001)
gfr	-0.039***	-0.036***	-0.029***	-0.047***
	(0.003)	(0.004)	(0.003)	(0.001)
_cons	0.045***	-0.002	0.042***	-0.012
	(0.002)	(0.008)	(0.008)	(0.012)
5 Groups Dummy	√	√	√	√
Number of obs	257371	182844	257371	182844
Root MSE	0.223	0.21909	0.21215	0.24468
Instrumented variables	wgrqdo wgrqeo grqdn grqen			
IV variables	l2br l3br l2be l3be l2bre l3bre l3lp			
First Stage Shea's Partial R-sq.*				
wgrqdo or Wgrqdif	--	0.0033	--	0.0002
wgrqeo	--	-	--	0.0003
grqdn	--	0.0174		0.0010
grqen	--	0.0127	--	0.0021
Sargan's (1958) and Basmann's (1960) tests of overidentification: P value	--	p = 0.0001	--	p =0.0007
Wooldridge (1995) Endogeneity Test: P value	--	p = 0.0000	--	p = 0.0000