# research paper series

**Globalisation, Productivity and Technology**

Research Paper 2004/01

***Firm Level Interactions Between Exporting and Productivity: Industry Specific Evidence***

**by**

David Greenaway and Zhihong Yu

The Centre acknowledges financial support from The Leverhulme Trust under Programme Grant F114/BF

Leverhulme Centre
for Research on Globalisation and Economic Policy

**The Authors**

David Greenaway is Professor of Economics and Director of the Leverhulme Centre for Research on Globalisation and Economic Policy; Zhihong Yu is a Research Postgraduate in the Leverhulme Research Centre for Research on Globalisation and Economic Policy, University of Nottingham.

**Acknowledgements**

The authors are grateful for financial support from The Leverhulme Trust under Programme Grant F114/BF. We would like to thank an anonymous referee and Richard Kneller for helpful comments on an earlier draft.

# Firm Level Interactions Between Exporting and Productivity: Industry Specific Evidence

**by**

**David Greenaway and Zhihong Yu**

**Abstract**

This paper investigates interactions between exporting and productivity at the firm level, using a panel of firms in the UK chemical industry. This is both highly technology intensive and the UK's largest exporting sector. We find exporters are more productive than non-exporters, but are also on average smaller. This superior productivity performance among exporters appears to be caused by both self-selection and learning-by-exporting effects. In contrast to other studies, we find learning effects are significantly positive among new entrants, weaker for more experienced exporters and negative for established exporters.

JEL classification: F14; D21; L65

Key words: Productivity, Learning by exporting, Self-selection

**Outline**

## Non-Technical Summary

What is the role of exports in productivity growth of individual firms? A robust finding in plant- or firm-level empirical studies is that exporters are more productive and larger than their purely domestic counterparts and this is explained by trade theorists in two different but mutually compatible hypotheses: self-selection or learning-by-exporting. Recently, a large and still rapidly growing literature grounded in country-specific empirical studies has tested these two hypotheses using plant- or firm-level data covering all manufacturing in a given country. However, one potential risk of such multi-industry studies is that they might have veiled the cross-industry heterogeneity of the link between exporting and productivity, since firm- and plant- level data from different industries are pooled together in one regression.

In this paper we investigate the causal link between exports and productivity by focusing on a panel of firms in UK chemical industry. This industry is an interesting case to take, because it is both highly research and development intensive and one of the UK's largest exporting sectors. More importantly, this industry has simultaneously experienced much faster growth in productivity and export intensity compared to the average manufacturing rate during the sample period. These industry characteristics make it an ideal candidate for examining export-productivity interactions.

To explore the causal link, we employ both linear probability and probit analysis to test the self-section hypothesis and use a dynamic panel instrument approach to quantify learning-by-exporting. In both tests, unobserved firm heterogeneity is controlled for in order to avoid spurious correlation between exports and productivity. On exploring learning-by-exporting, we also distinguish between exporting firms with different export histories to see how productivity effects of exports rely on firms' past exporting experience.

Unlike previous multi-industry studies, in this industry we find that exporters are on average smaller than non-exporters and size is not positively related to a firm's probability of exporting. Like other studies, we find that exporters are more productive and the productivity gap between exporters and non-exporters is greater than those in all other manufacturing activities. The superior productivity performance among exporters seems to be explained by both self-selection and learning-by-exporting. Increases in TFP significantly increase the probability of exporting and we also find that the association between lagged exports and productivity is positive and significant. These results offer some support for the existence of learning forces based on self-selection into the global market. Finally, in contrast to some other studies, we find that the learning effect is strongest among new export market entrants, diminishing as export experience increases and becomes negative for established exporters.

# 1 INTRODUCTION

An important contribution of 'new trade theory' as synthesised by Helpman and Krugman (1985) was the emphasis on the firm in the determination of trade flows. In turn, this facilitated an emphasis on the key role of scale economies and imperfect competition in shaping the volume and pattern of intra-industry trade. Important as they are however, new trade theory models are generally based on a representative firm framework, where all firms are symmetric in terms of size, productivity and exports. It is only recently that economists have begun to focus on an entirely new dimension namely, firm productivity heterogeneity and the role it might play in the composition of trade. Melitz (2003), Helpman, Melitz and Yeaple (2004) and Jean (2002) are all important contributions to this 'new exporting / heterogeneous firm trade theory' literature.

Understanding the interactions between export behaviour and firm productivity is also important from a policy standpoint. Policymakers have long been convinced that export promotion is beneficial to economic growth. The evidence base for this has been largely from cross-country studies. However, without robust *micro*economic evidence about any causality between productivity and exports, it is difficult for policymakers to set appropriate export promotion policies targetted at boosting firm productivity and ultimately economic growth.

A growing body of empirical studies have found consistent evidence that exporters are typically larger and more productive than non-exporters. Examples include, Aw and Hwang (1995), Bernard and Jensen (1999), Bernard and Wagner (1997), Clerides, Lach and Tybout (1998), Greenaway and Kneller (2003), Greenaway, Gullstrand and Kneller (2003), Delgado, Fariñas and Ruano (2002), Castellani (2002) and Wagner (2002). The analytical literature to explain the significant productivity gap between exporting firms and their domestic counterparts was pioneered by Bernard and Jensen (1999) who outlined two alternative but not mutually exclusive hypotheses. One is self-selection. Firms self-select into export markets according to their productivity level, because of the presence of sunk costs. Simply put, if export profit increases in productivity, then only firms with higher productivity than a certain threshold find it profitable to export. Thus, costs like distribution and establishing service networks in the foreign market, generate an export barrier for low productivity firms so they remain purely domestic. More recently, Melitz(2003) and Helpman, Melitz and Yeaple (2004) have built general equilibrium dynamic industry models to show how the industry entry and export productivity threshold is determined by within sector productivity distribution and trade costs. So exposure to trade induces only firms with higher productivity than the threshold to enter the export market, leaving less productive firms to operate only in the domestic market, and simultaneously force the least productive firms to cease producing.

The second explanation is the learning-by-exporting hypothesis. This suggests that breaking into the export market can make firms more productive due to the knowledge flows from international buyers and competitors to exporters. This is supported by some industry studies that document knowledge flows from foreign buyers to exporting firms and technology spillovers in international markets, for example World Bank (1993) and Rhee, Ross-Larson and Pursell (1984). Empirically this view focuses on *post-entry* performance. Thus, firms that enter and stay should enjoy faster productivity growth and higher productivity levels than their domestic counterparts *after* entry. The transmission channels could include fiercer competition in foreign markets and learning from international buyers and competitors.

This paper reports on an investigation of these two hypothesis based on a firm-level panel data set for the chemical industry in United Kingdom. This is an interesting case to take for several reasons. First, this is one of the UK's largest manufacturing sectors and its biggest exporter. Second, it is one of the UK's most technology intensive sectors with high productivity growth rates over the last decade. Third, it is a mature exporting sector. Finally by focusing on a particular industry in a given country, we can avoid the potential for cross-industry effects to complicate causality links between exporting and productivity.

We deploy both a linear probability model with fixed effects and a probit regression to examine the self-selection hypothesis. To test the learning by exporting hypothesis, we use a first-differenced specification with appropriate instruments. Our key findings are that exporters are *smaller* but more efficient than purely domestic firms. This is a surprising finding but chimes with results reported by Wagner (2003). There is strong evidence that firms self-select into export markets. But there is also evidence that they learn from exporting. The learning effect depends on firms' exporting experience. In contrast to Kraay(1999). We find that the learning effect is significant and positive for new entrants, less significant for more experienced exporters and negative for established exporters.

The remainder of the paper is organized as follows: Section 2 outlines the characteristics of the chemical sector and contrasts it with other manufacturing sectors. Section 3 explains our modelling and estimation strategy. This Section also analyses our results. Finally, Section 4 concludes.

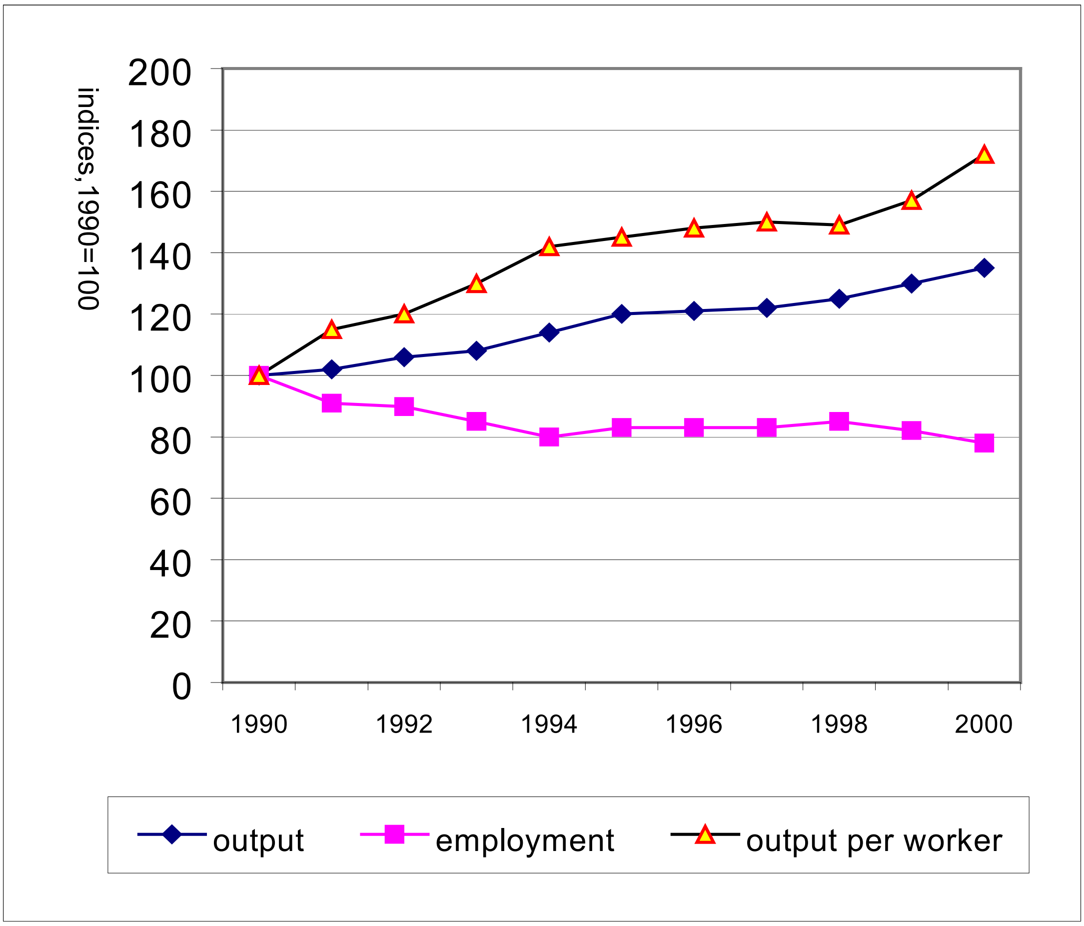
# 2 THE UK CHEMICAL INDUSTRY

## 2.1 Characteristics of the chemical industry

According to the DTI (Department of Trade and Industry) and the CIA (Chemical Industry Association), the UK chemical industry is the country's largest manufacturing sector. It employs more than 400,000 workers, producing and selling a diverse range of materials and products worth over £40 billion annually. It accounts for 13% of the value added of UK manufacturing. It is also the UK’s largest exporter, with gross exports of £25.8 billion and net exports of £4.6 billion in 2000.

The industry is highly research based and technologically advanced, with significant expenditure on research and development. In 1997, R&D expenditure, at £2.8 billion, was 8.7% of total sales, almost six times as high as in other manufacturing activities. From 1990 to 2000, productivity, measured by output per worker, has risen by more than 5% annually (see figure 1) and annual output growth achieved 3%, five times as high as the average manufacturing growth rate and the second highest among all manufacturing sectors.

**Figure 1** UK chemical industry employment, output and productivity, 1990-2000




*Source : UK chemical Industry association ,* *www.chemical-industry.org.uk*

## 2.2 Data

Our data is a sub-sample of UK firm level panel data from the *OneSource* database[1]. This is an unbalanced panel on 461 firms from 1989 to 1999, yielding a total of 2,883 observations. Data coverage includes 5-digit SIC code, year, employment, real turnover, real wages, real exports, real fixed assets and real value added for each firm. All values are deflated by disaggregated price deflators. Firm-level productivity is measured by TFP, labour productivity and AVC (average variable cost). We generate firm level TFP indices as residuals from three factor, constant returns, Cobb-Douglas regressions. Labour productivity is measured as gross real output per worker, and AVC as the sum of real labour and material costs divided by real sales.

[1] For the description of the original dataset, refer to Girma, Greenaway, Kneller (2004), pp 5.

## 2.3 Exporters versus non-exporters

Figure 2 reports shares of exporters and non-exporters in total firms, total output and employment from 1989 to 1999. As can be seen, exporters did not exceed non-exporters in any of these indicators until 1996. In 1989 more than 80% of all firms were non-exporters, produced more than 80% of total output and employed more than 80% of the workforce. However, the differences between the exporter and non-exporter groups became smaller in subsequent years. In 1990, exporters' share of firm numbers jumped to over 35% and to 45% in 1996. This trend continued and from 1997 onwards exporters outweigh non-exporters in terms of all three indicators.

Table 1 compares the mean firm performance differential between exporters and non-exporters in chemicals with those of all other manufactures. On average, chemical exporters are *smaller* than non-exporters by 10-15 percent, but more efficient and pay higher wages. Exporting firms produce 10% less output, gain 13% less value added, and employ 14% fewer workers on average. However, they are more productive in terms of all three productivity measures. For example, the mean of TFP for exporters is 4.5% higher than the industry mean, whereas that for non-exporters is 3.4% below it. Exporting firms also pay 7.6% higher wages than domestic producers.

Looking at manufacturing more generally, exporters are also more productive and pay higher wages, but are *larger* than non-exporters by 10-11%. They produce 10% more output, gain 10.6% more value added, employ 11% more workers and pay 1.5% higher wages. The mean level of labour productivity and TFP of exporters are 3.5% and 6.4% higher than non-exporters, respectively.

**Table 1:** ***Average firm performance for exporters and non-exporters, 1989-1999***

| **Performance** | **Other manufacturing** | | | **Chemical** | | |
|---|---|---|---|---|---|---|
| | Exporters | Non-exporters | Differential* % | Exporters | Non-exporters | differential % |
| Sales | 14903 | 13488 | 10 | 23363 | 26070 | -10 |
| Employment | 205.41 | 184.33 | 11 | 193.70 | 226.72 | -14 |
| Wage | 15.300 | 15.072 | 1.5 | 16.749 | 15.56 | 7.6 |
| Value added | 4873.6 | 4405.0 | 10.6 | 6431.1 | 7397.8 | -13 |
| AVC | 0.63568 | 0.64624 | -1.7 | 0.704 | .719 | -2 |
| Labour productivity | 77.139 | 74.496 | 3.5 | 112.45 | 106.61 | 5.4 |
| TFP | 0.033 | -0.031 | 6.4 | 0.045 | -0.034 | 7.9 |

* Differential is defined as the (exporter performance – nonexporter performance) / (non exporter performance) except for TFP. TFP differential is defined as exporter TFP – nonexporter TFP

Table 2 reports on the persistence of export status. Over the sample period 91% of exporters continue to export and 96% of non-exporters continue to operate only in the domestic market. On the other hand, only 4.5 % of current exporters quit and 9% of current non-exporters enter in the next period. Similar results emerge in other manufactures, but the probability of entering and quitting are higher than those in the chemical sector.

**Table 2:** ***Transition matrix for exporting status*** **(%)**

| | **Chemical** | | **Other manufactures** | |
|---|---|---|---|---|
| | Not-exporting at t+1 | Exporting at t+1 | Not Exporting at t+1 | Exporting at t+1 |
| Not Exporting at t | 90.83 | 9.17 | 93.46 | 6.54 |
| Exporting at t | 4.45 | 95.55 | 4.41 | 95.59 |

# 3 MODELLING STRATEGY AND RESULTS

## 3.1 Export Premia

To eliminate cross industry effects and focus on within industry differences between exporters and non-exporters, we start by examining export premia, controlling for industry and time effects. The specification used to do so is :

$$Y_{it}=\alpha+\chi E_{it}+\beta_1 Industry_{it}+\beta_2 Year_t+\varepsilon_{it} \qquad (1)$$

where $Y_{it}$ denotes some aspect of firm performance (such as log of employment, real sales, value added , capital intensity and a measure of productivity). $E_{it}$ is a dummy for current export status, $Year_t$ and $Industry_{it}$ are sets of time and 4 digit SIC industry dummies and $\varepsilon_{it}$ is assumed to be a well-behaved zero-mean disturbance term. The coefficient $\chi$ then indicates the export premium in terms of firm performance.

Results from estimating equation (1) are reported in Table 3. For firms in all other manufacturing sectors, the results are similar to those reported by Girma, Greenaway and Kneller (2004). Exporters are larger, more efficient and pay higher wages. However, export premia in the chemical sector differ from that in other manufactures in two respects. Firstly, there is no evidence that exporters are significantly larger than non-exporters. In fact their employment is 3.7% lower and statistically insignificant. Secondly, the productivity export premium in the chemical industry is significantly positive and greater than those in other manufactures. For example, exporters are 10.4% more productive in terms of output per worker and 9.1% more efficient in terms of TFP, whereas in other manufactures the labour productivity and TFP differential is just 7.5% and 7.4%, respectively. Exporters' superior labour productivity performance can be partly explained by the higher capital-intensity in exporting firms, since exporters are 20% more capital-intensive than non-exporters. But even controlling for this, we still find exporters are 7% more productive.

A striking finding is that exporters are on average smaller than non-exporters, especially combined with the fact that they are substantially more efficient. This result is inconsistent with the findings in almost all previous empirical studies mentioned in Section 1. It is also inconsistent with the predictions from recent models. Melitz (2003), Helpman, Melitz and Yeaple (2004) and Jean (2002) demonstrate that under monopolistic competition more efficient firms charge lower prices. Since gross output is decreasing in product price for individual firms, exporters should be larger than their domestic counterparts. However, as Wagner (2003) has recently argued, cross industry analyses typically do not control for unobserved firm heterogeneity. When he does so for three German industries, the size-export nexus disappears. Our results further vindicate a focus on specific industries given the potential for bias in multi-industry analyses.

**Table 3** ***Export premia and firm performance***

| Performance | Other manufactures | Chemical |
|---|---|---|
| Employment | 0.321*** | -0.037 |
| | (4.57) | (-0.85) |
| Capital Intensity | 0.247*** | 0.208 *** |
| | (5.05) | ( 5.45) |
| Wage | 0.0446*** | 0.0643*** |
| | (6.98) | (5.39) |
| Value added | 0.283*** | 0.008 |
| | (5.67) | (0.16) |
| AVC | -0.0146** | -0.020** |
| | (7.39) | (-2.06) |
| Labour productivity | 0.0756*** | 0.104*** |
| | (5.34) | (3.97) |
| TFP | 0.074*** | 0.091** |
| | (4.29) | (2.91) |

***: significant at 1% **: significant at 5% *: significant at 10%

### 3.2 Self-selection effect

Bernard and Jensen(2001) show that the decision to export by a profit-maximising firm can be modelled using a binary choice non-structural approach :

$$E_{it} = 1 , \quad if \;\; \alpha \mathbf{Z}_{it} + FE_{it-1} - F + \varepsilon_{it} \geq 0$$
$$0, \quad otherwise \qquad (2)$$

where $E_{it}$, $E_{it-1}$ , $F$ and $\mathbf{Z}_{it}$ denote current exporting status, lagged exporting status, fixed export cost and firm characteristics such as size and productivity, respectively. Previous studies have applied a number of microeconometric approaches to estimate Eq.(2). [1] In this paper, we choose the IV-difference linear probability approach suggested by Bernard and Jensen(1999)[2], and use probit regression to provide a robustness check. The specification for the linear probability model is:

$$E_{it} = \kappa + \alpha Size_{it-1} + \gamma Human\text{-}capital_{it-1} + \chi Productivity_{it-1} + \theta E_{it-1} + \mu_i + \eta_{it} \qquad (3)$$

Where log of employment or output and log of wage are used as proxies for size and human capital, respectively. Productivity is measured as TFP, output per worker and AVC. $\mu_i$ reflects unobserved firm heterogeneity such as managerial ability and proprietary technology. To get consistent estimators of the firm performance characteristics, the first difference form of [3] is estimated as:

$$\Delta E_{it} = \alpha \Delta Size_{it-1} + \gamma \Delta\, Human\text{-}capital_{it-1} + \chi \Delta Productivity_{it-1} + \theta \Delta E_{it-1} + \Delta \eta_{it} \qquad (4)$$

[1] The key issue is the assumption about the disturbance term $\varepsilon_{it}$. The simplest approach is to take $\varepsilon_{it}$ as independent standard normal disturbances. Nonetheless, since persistent unobserved plant characteristics such as managerial ability can make some firms consistently higher productivity or consistently prone to exporting, it is more appropriate to model the disturbance term $\varepsilon_{it}$ as composed of unobserved plant effects , $\mu_i$ , plus transitory term $\eta_{it}$. Apparently, if $\varepsilon_{it} = \mu_i + \eta_{it}$ , then the standard Probit regression is inappropriate . The new problem is whether the plant effect $\mu_i$ is random or fixed. If $\mu_i$ is assumed to be random , then the random effect Probit estimator suggested by Heckman (1981) could apply. Otherwise, if the unobservable plant effect is fixed, then unfortunately there is no feasible ways to remove the heterogeneity in Probit model so far (Greene ,2000 ). The alternative approach is to use linear probability model with fixed effects. In previous studies, Probit regression is employed in Girma, Greenway and Kneller (2004), linear probability model with and without fixed effect is applied in Bernard and Jensen(2001) , while Roberts and Tybout(1997) use Probit model with random effect.

[2] For discussion of the advantage and weakness of the linear probability approach and other alternative approaches on estimation of Eq.(2), please see Bernard and Jensen(2001).

where second and third order of the lags of the levels of the explanatory variables, $Size_{it-2,-3}$, Human-capital $_{it-2,-3}$, $Productivity_{it-2,-3}$ and $E_{it-2,-3}$, are used as instruments.

Table 4 reports the results from Eq.(4) , as well as from a probit regression using the same regressors. Column 1 reports the coefficients of firm characteristics and lagged exporting status from the IV-first difference linear probability model.[3] Employment and wages are negatively and insignificantly correlated with the probability of exporting. A 10% increase in employment and wages lowers the probability of exporting by 1.6% and 2.1% respectively but is statistically insignificant at conventional levels. However, higher TFP does lead to higher exporting probability. For a 10% increase in TFP the probability of exporting increases by 5% and this is significant at the 5% level. Previous exporting status remains a powerful predictor of current exporting probability, exporting in the previous period increases the probability of exporting by 70%. This indicates that export status is quite persistent over time, which is generally taken as evidence of the presence of significant sunk export entry costs. Results from the probit model are consistent with this.

So an interesting pattern is revealed in this particular industry: productivity plays a far more important and positive role than firm size in the determination of the export decision. These results strongly support the self-selection hypothesis. However, in contrast to other studies like Girma, Kneller and Greenaway (2004) and Bernard and Jensen (1999) we find no evidence that larger firms have an advantage.

**Table 4 : *Determinants of firm's decision to export***

Dependent variable: Exporting Status

| | Linear Probability (First difference IV) | Probit |
|---|---|---|
| Employment | -0.162 | -0.0265* |
| | (-0.83) | (-1.83) |
| Wage | -0.215 | -0 .0338 |
| | (-1.01) | (-0.61) |
| TFP | 0.529** | 0.294** |
| | (2.01) | (2.94) |
| Previous exporting status | 0.699*** | 0.867*** |
| | (5.79) | (82.6) |
| Year dummy | yes | no |

***: significant at 1%**: significant at 5%*: significant at 10%

[3] For brevity, only the results using TFP as productivity measure are reported. Results of AVC and output per labour follow the same pattern and can be obtained from the author upon request.

### 3.3 Learning by exporting

The simplest test of whether exporting can boost productivity is to regress current productivity performance on past exports. In previous studies, a number of different approaches from GMM (Clerides, Lach and Tybout 1998) to matching (Girma, Greenaway and Kneller 2003 and Greenaway and Kneller 2003) have been applied. In this paper, we employ the dynamic panel instrument approach from Kraay (1999) to investigate the effect of first order lagged exports on current productivity level[4]:

$$Y_{it}=\alpha Y_{it-1}+\chi X_{it-1}+ \mu_i+\eta_t+\varepsilon_{it} \quad (5)$$

Where $Y_{it}$ , $Y_{it-1}$and $X_{it-1}$ denote productivity performance , lagged productivity performance and lagged export intensity respectively, $\mu_i$ and $\eta_t$ are firm specific and time-specific effects, $\varepsilon_{it}$ is then a well-behaved zero mean disturbance , which is assumed to be independent of $X_{it-1}$ and not serially correlated. $Y_{it-1}$ is included as an explanatory variable to eliminate the effect of serial dependence in productivity.

Equation [5] is estimated using the Kraay (1997) method.[5] Our results are reported in Table 5. The coefficient of lagged exports is positive and statistically significant at the 10% level, which implies that exporting in the last period might increase current productivity, possibly due to learning by exporting. The magnitude of this possible learning effect is also non-trivial. A 10% increase in exports is associated with a 1 percent increase in TFP and 5.6 percent increase in labour productivity in the next

4 According to Kraay (1999), even if one could find a significant positive correlation between previous exporting experience and current productivity performance, this positive effect is not necessarily resulted from learning effect , because there exist two alternative possible explanations. The first alternative explanation is that unobservable plant characteristic may affect both enterprise performance and exports, which can lead to a spurious correlation between productivity level and past exporting status. The second alternative explanation is that productivity performance may be serially correlated over time and is jointly determined with exports. To rule out the above two alternative explanations, it is necessary to include the lagged dependant variable and the fixed firm specific effect into the explanatory variables.

5 As was shown in Kraay(1999), to get consistent estimators of $\alpha$ and $\chi$ in the presence of $\mu_i$ and $\eta_t$ , the following strategy is used. First, in order to purge the time effect $\eta_t$, retrieve the residuals from the regression of Y and E on a set of time dummies. This yields $Y^*_{it}$ , $Y^*_{it-1}$ and $E^*_{it-1.}$ Second, we take first differences of $Y^*_{it}$ , $Y^*_{it-1}$ and $X^*_{it-1}$ to eliminate unobserved firm heterogeneity $\mu_i$ and estimate the specification: $\Delta Y^*_{it} = \alpha\Delta Y^*_{it-1} + \chi\Delta X^*_{it-1} + \Delta\varepsilon_{it}{}^*$

Since the first differencing results in a correlation between the residual and explanatory variables on the left hand side, second and higher order lags of Y and E are used as instruments for $\Delta Y^*_{it-1}$ and $\Delta E^*_{it-1}$.

period. The last row of table 5 shows that there is no serial correlation in $\varepsilon_i$* for TFP and labour productivity. The coefficient of lagged exporting is also positive when productivity is measured by AVC, which indicates a negative effect of previous exporting on current productivity. But as pointed out by Clerides Lach and Tybout (1998), since average variable cost does not include capital cost, learning effects might be missed if the exporting firms are labour intensive and efficiency gains are captured by workers in higher wages. On the other hand, the P-value for AVC rejects the null hypothesis that there is no serial correlation in $\varepsilon_{it}$*. So the dynamic panel instrument methodology is not a perfect approach for the test of learning-by-exporting, if productivity is measured by AVC.

**Table 5** ***Results for learning by exporting***

Dependent Variable : Productivity

| **Measure of Productivity** | **TFP** | **Labour productivity** | **AVC** |
|---|---|---|---|
| Lagged Productivity | 0.349***<br>(3.24) | 0.134***<br>(5.88) | -0.323***<br>(-10.74) |
| Lagged exports | 0.0987**<br>(1.73) | 0.562*<br>(1.44) | 0.304*<br>(0.074) |
| P-value for serial correlation in $\varepsilon_{it}$* | 0.77 | 0.36 | 0.033** |

These results raise the question of whether any learning effects depend on the firm's previous export experience i.e. does the magnitude and significance of $\chi$ vary with past export experience. Girma, Greenaway and Kneller (2004) find that output and labour productivity growth rates of exporters are highest in the first year after entry and become smaller and insignificant in the second year. So if learning by exporting only occurs in the first few years after a firm breaks into the export market $\chi$ should be positive and significant among new entrants but insignificant for earlier entrants with more export experience. To explore this, in line with Kraay (1999) we firstly classify the firms into: established exporters, export market entrants, switchers, exiters and non-exporters.[6] Since we are particularly interested in whether learning effects depend on firms' past exporting experience, we excluded exiters and switchers from

[6] In Kraay(1999) , firms are classified into five types of export history: Established exporters that export during the whole sample period, entrants that initially do not export but start exporting at some point during the sample, exiters that initially export but quit the export market later and switchers that switch their export status , and non-exporters that never export.

the sample and separate entrants further into three types of firms for a given time point *t*: (a) New entrants: entrants which started exporting at t-1. (b) Entrants with 2 years of exporting experience: entrants that start exporting at t-2. (c) Entrants with at least 3 years of exporting experience: entrants that start exporting prior to time t-2. Hence we particularly focus on the following five types of firms defined in Table 6.

**Table 6:** ***Definition of Different Types pf Firms according to their past exporting experience at time t***

| Type of firms | Export status at and prior to period t -4 | Export status at t -3 | Export status at t -2 | Export status at t and t –1 |
|---|---|---|---|---|
| New entrants | 0 | 0 | 0 | 1 |
| Entrants with 2 years of export experience | 0 | 0 | 1 | 1 |
| Entrants with at least 3 years of export experience | 0 or 1 | 1 | 1 | 1 |
| Established exporters | 1 | 1 | 1 | 1 |
| Non exporters | 0 | 0 | 0 | 0 |

To investigate how any learning effect varies with exporting firms with different export experience, Eq. [6] is modified to regress current productivity level on lagged export intensity, allowing the coefficients on lagged exports to vary with different types of firm.

$$Y_{it}=\alpha Y_{it-1}+[\chi^1 G^1 + \chi^2 G^2 + \chi^3 G^3 + \chi^4 G^4]X_{it-1} + \mu_i + \eta_t + \varepsilon_{it} \qquad (6)$$

t=1992 ,1993…, 1999

*X* represents export intensity. $G^1$ , $G^2$ , $G^3$ and $G^4$ represent dummies for new entrants, entrants with two year export experience, entrants with more than two years experience and established exporters respectively. So $\chi i$ (i=1,2,3,4) represents the learning effect for different types of firms. The results of estimation are reported in Table 7[7].

[7] To purge the time effect and the firm heterogeneity effects and get consistent estimators for $\alpha$ and $\chi^i$, the same transformation as Eq.(5) can be applied to Eq.[6]:
$\Delta Y^*_{it} = \alpha \Delta Y^*_{it} + [\chi^1 G^1 + \chi^2 G^2 + \chi^3 G^3 + \chi^4 G^4] \Delta X^*_{it-1} + \Delta\varepsilon_{it}^*$ , t=1992 ,1993…, 1999
where second and higher order lags of Y, $Y_{it-2}$ $Y_{it-3}$ , and X interacted with $G^i$ ($G^i \cdot X_{it-2}$, $G^i \cdot X_{it-3}$ )are used as instruments.

**Table 7 :** ***Results of learning effect controlling for past export experience***

| Type of firms | Coefficient |
|---|---|
| Established exporters | -0.113***<br>(2.45) |
| Entrants with at least 3 years of export experience | 0.012<br>(0.68) |
| Entrants with just 2 years of export experience | 0.090*<br>(1.36) |
| New entrants | 0.213**<br>(3.14) |

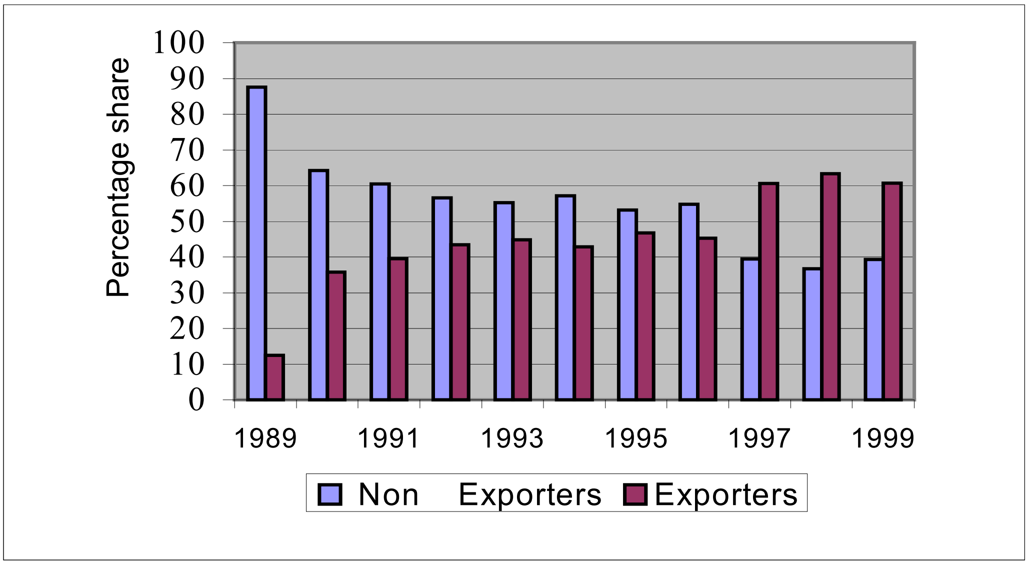
For new entrants with only one year's export experience, a 10% increase in export intensity improves TFP in the following year by 2%. But for exporters with two years and more than two years export experience, the learning coefficient is only 0.9% and 0.1% , respectively, and is statistically insignificant at the 5% level. Furthermore, for established exporters with many years of experience, the learning effect is even negative. These results indicate that more experienced exporters reap less productivity gains from learning effects, which is contrary to the findings in Kraay (1999). However, it is consistent with the intuition that learning-by-exporting is more likely a one-off effect which only occurs in the first few years post-entry and diminishes as the firm's exporting experience increases, rather than being a cumulative process. Since established exporters are those firms which have successfully survived competition in export markets for many years, they may have already exhausted the benefits of learning.

# 4 Conclusions

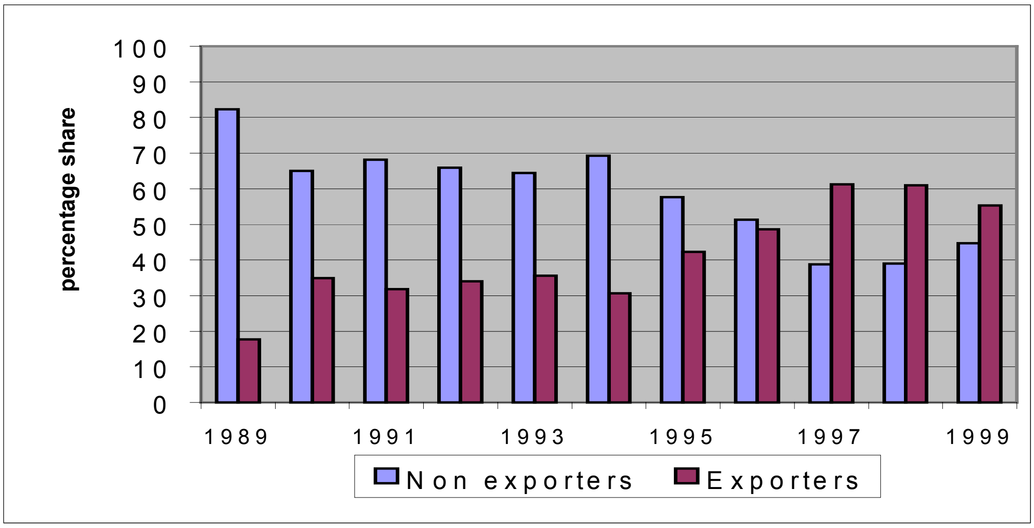
In this paper, we have evaluated the links between exports and productivity at the firm level, focusing on a technology intensive UK industry which is a large exporter and has experienced high productivity growth over the last decade. We find that exporters are more efficient than their purely domestic counterparts, although they are on average smaller. Moreover, the productivity differential between exporters and non-exporters is greater than those in other manufactures. The superior productivity performance among exporters can be explained by both self-selection and learning-by-exporting effects. Estimating both a linear probability and probit model, we find that increases in TFP significantly increase the probability of exporting. We also find that the association between lagged exports and current productivity is positive and significant. These results offer some support for the self-selection and learning by exporting hypotheses. Finally, in contrast to Kraay (1999), we find the learning-by-exporting effect is strongest among new entrants, weaker for firms with more past export experience and becomes negative for established exporters.

**Figure 2** *Shares of exporters and non exporters in Chemical Sector,1989-1999*

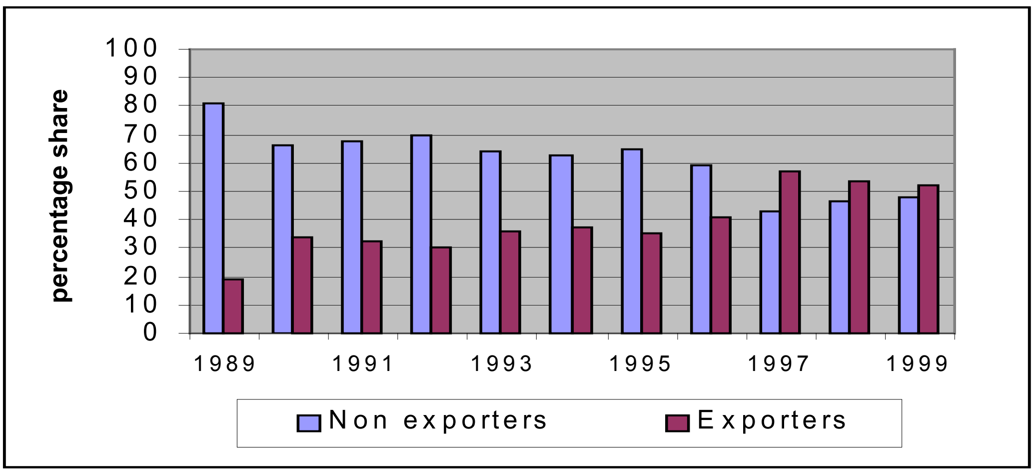
Panel 1 : Share of firm number : Exporters VS. Non exporters




Panel 2 : Share of output : Exporters VS. Non exporters




Panel 3: Share of employment : Exporters VS. Non exporters



## References


Aw, Y., Chung and Roberts, K. (1995), 'Productivity and the Decision to Export: Micro Evidence From Taiwan and South Korea' *NBER Working Paper 6558*, National Bureau of Economic Research, Cambridge, Mass.

Aw, Y. and Hwang, B. (1995), 'Productivity and the Export Market: A Firm Level Analysis', *Journal of Development Economics*, Vol. 47, pp.313-332.

Bernard, A. and Jensen, B. (2001), 'Why Some Firms Export*?' NBER Working Paper 8349*, National Bureau of Economic Research, Cambridge, Mass.

Bernard, A. and Jensen, B. (1999), 'Exceptional Exporter Performance: Cause, Effect, or Both?', *Journal of International Economics*, Vol. 47, pp.1-25.

Bernard, A. and Wagner, J. (1997), 'Exports and Success in German Manufacturing' *Weltwirtschaftliches Archiv* , Vol. 133, pp.134-157.

Castellani, D. (2002), 'Export Behaviour and Productivity Growth: Evidence from Italian Manufacturing Firms, *Weltwirtschaftliches Archiv*, Vol. 138, pp.605-628.

Clerides, M., Lach, S. and Tybout, J. (1998), 'Is Learning by Exporting Important? Micro-Dynamic Evidence From Colombia, Mexico and Morocco', *Quarterly Journal of Economics*, Vol. 113, pp.903-904.

Delgado, M., Fariñas, J., Ruano, S., (2002), 'Firm Productivity and Export Markets: A Non-parametric Approach', *Journal of International Economics*, Vol. 57, pp.397-422.

Evenson, R. and Westphal, L. (1995), 'Technology Change and Technology Strategy' *Handbook of Development Economics*, Vol. 3 (Amsterdam, North-Holland).

Girma, S., Greenaway, D. and Kneller, R. (2003), 'Export Market Exit and Performance Dynamics: A Causality Analysis of Matched Firms', *Economics Letters*, Vol. 80, pp.181-187.

Girma, S. Greenaway, D. and Kneller, R. (2004), 'Does Exporting Lead to Better Performance? A Microeconometric Analysis of Matched Firms', *Review of International Economics* (forthcoming).

Greenaway, D., Gullstrand, J. and Kneller, R. (2003), 'Exporting May Not Always Boost Firm Performance' *GEP Research Paper 03/26*, University of Nottingham

Greenaway, D and Kneller, R. (2003), 'Exporting, Productivity and Agglomeration : A Difference in Difference Analysis of Matched Firms' *GEP Research Paper 03/45*, University of Nottingham

Greene, A. (2000), '*Econometric Analysis'*, Fourth Edition, Prentice Hall International.

Heckman, J. (1981), 'Statistical Models for Discrete Panel Data*',* in *Structural Analysis of Discrete Data with Econometric Applications,* eds. C.F. Manski and D. McFadden, Cambridge: MIT Press, pp.114-178.

Helpman, E., Krugman, P. (1985), Market Structure and Foreign Trade, Cambridge: MIT Press.

Helpman, E., Melitz, M. and Yeaple, S. (2004), 'Export versus FDI', *forthcoming in American Economic Review.*

Jean, S. (2002), 'International Trade and Firms' Heterogeneity Under Monopolistic Competition', *Open Economies Review*, Vol. 13, pp. 291-311.

Kraay, A.(1999), 'Exports and Economic Performance: Evidence from a Panel of Chinese Enterprises', *Revue d' Economie Du Developpement*, Vol.1-2, pp.183-207.

Meltiz, M. (2003), 'The Impact of Trade on Intra-Industry Reallocations and Aggregate Productivity*, Econometrica* , Vol. 71 , pp.1695-1725.

Rhee Ross-Larson and Pursell (1984), *Korea's Competitive Edge: Managing the Entry into the World Markets* (Johns Hopkins University Press).

Roberts, K. and Tybout, J. (1997), 'The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs', *American Economic Review*, Vol.87, pp.545-564.

Wagner, J. (2003), 'Unobserved Firm Heterogeneity and the Size-Export Nexus', *Review of World Economics/Weltwirtschaftliches Archiv*, Vol. 139, pp.161-172.

Wagner, J. (2002), 'The Causal Effect of Exports on Firm Size and Labour Productivity', *Economics Letters*, Vol. 77, pp.287-292.

Wagner, J. (2001), 'A Note on the Firm Size-Export Relationship', *Small Business Economics*, Vol.17, pp.229-237.

World Bank (1993), *The East Asian Miracle* (New York: Oxford University Press 1993).