Interaction between exporting and productivity at firm level: Evidence from the UK chemical industry

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Abstract

This paper investigates the interaction between exporting and productivity at firm level , using a panel of firms in UK chemical industry which is highly technology intensive and the largest UK manufacturing exporter. We find exporters are on average smaller but more productive than non-exporters. Applying empirical techniques from Bernard and Jensen(2001) and Kraay(1999), we find the superior productivity performance among exporters is caused by both self-selection and learning-by-exporting effect. In contrast to other studies, we find learning effect is significantly positive among new entrants, weaker for earlier entrants and negative for established exporters.

1 Introduction

Conventional trade theory based on comparative advantage has received considerable scepticism for its lack of the ability to explain the trade pattern in the real world. In the last few decades, therefore, trade economists （ Krugman 1980，Helpman and Krugman 1985） have developed new trade theory, which places the firm in the central place of trade theory , to stress the important role of scale economies and imperfect competition in the determination of trade pattern, particularly in manufactures trade among industrial countries. However, new trade theory models are based on a representative firm framework , in which all firms are symmetric in terms of size, productivity, export etc. .It is not until recently economists begin to identify a new dimension ,namely, firm productivity heterogeneity, that might play an important role in the composition of trade but is ignored by standard new trade theory.(Melitz 2002, Helpman , Melitz and Yeaple 2002 , Cleridas , Robert and Tybout 1998,Bernard and Jensen 2001). In order to reveal the theoretical relationship between firm heterogeneity and intra-industry trade pattern, it is crucial to empirically investigate the causal link between productivity and export at micro level.

On the other hand, the interaction between export behaviour and firm productivity also has its important policy implications. Policymakers believe that export promotion is beneficial to macro economic growth. There are plausible reasons to believe that exports can serve as a conduit for technology transfer from advanced countries , which boost the productivity level of the whole economy through spill over effect, and thus contribute to sustained rates of output growth in the long run. However, without robust microeconomic evidence about the causality between productivity and exports , it is difficult for policymakers to set appropriate trade policies such as export promotion strategies aiming to boost growth through exporting.

A growing body of empirical studies have found consistent evidence that exporters are larger and more productive than their domestic counterparts(Aw&Chang 1998, Bernard and Jensen 1997, Chen&Tang 1987, Clerides ,Lach and Tybout 1998 , Girma , Greenaway and Kneller 2001, Delgado,Farinas and Rano 2002). The analytical literature to explain the significant productivity gap between exporting firms and their domestic counterparts are pioneered by Bernard and Jensen (1999) in which they outlined two alternative but not mutually exclusive hypothesis on the causal link between productivity and exporting. One is the self-selection hypothesis , which means firms self-select into export market depending on their productivity level. The other is learning-by-exporting hypothesis , which suggests breaking into the export market can make firms more productivity due to the knowledge flows from international buyers and competitors to exporters. The exceptional performance of exporters can be explained by either of them, or both.Our study aims to investigate these two hypothesis based on a firm-level panel data set for the chemical industry in United Kingdom. The chemical sector is UK's largest exporter and manufacturing sector, as well as one of UK's most technology intensive sector with high productivity growth rate over the last decade. These two features make it interesting to investigate the microeconomic linkage between exporting and productivity in this specific industry. By focusing on this a particular industry in a given country, we can avoid the influence of cross-industry effect that may complicate the causality between export and productivity.

We employ both linear probability model with fixed effect and probit regression to examine the self-selection hypothesis. To test learning by exporting hypothesis, We use a first-differenced specification with appropriate instruments developed by Kraay(1999), and make some modifications on his approach to reveal how learning effects , which is revealed by the association between lagged exporting and current productivity , vary with firms which enter the export market at different periods. In this particular industry, our key finding is exporters are smaller but more efficient than purely domestic firms. There is strong evidence that firms self-select into export market depending on their productivity , as well as learn from exporting. The learning effect depends on firm's exporting experience. In contrast to Kraay(1999), We find that learning effect is negative for established exporters but positive for new entrants. Moreover, earlier entrants are less likely to reap productivity gains from lagged exporting.

This paper is organized as follows. section two reviews the theoretical framework and empirical evidence on the causality between exporting and productivity in previous literature. Section three outlines the characteristics of chemical sector compared to other manufacturing sectors. Section four and five show the empirical methodology and analyse the empirical results . section six concludes.

2 Productivity heterogeneity and export decision : causal links

Building on the work of trade hysteresis literature (Baldwin1990, Dixit1989, Baldwin and Krugman 1989) , Roberts and Tybout (1997),Cleridas, Lach and Tybout (1998) and Bernard and Jensen(2001) setup partial equilibrium dynamic models to analyse the decision to export by multi-period forward-looking firms. These models explain why the presence of sunk export fixed cost will lead to self-selection and hysteresis effect. Simply put, if profit increases in productivity, only firms with higher productivity level than certain threshold can find it profitable to export. Because more productive firms are able to achieve sufficiently high export profit to cover the sunk export fixed cost so as to gain positive net profit through exporting. On the other hand, the sunk export fixed costs , such as distribution and service network costs in the foreign market, generate an export barrier for low productivity firms by making them unprofitable to export so as to remain purely domestic. More recently , Melitz(2002) and Helpman, Melitz and Yeaple (2002) built general equilibrium dynamic industry model to show how the industry entry and export productivity threshold is determined by with-in sector productivity distribution and trade costs. So the exposure to trade will induce only the firms with higher productivity than the threshold to enter the export market , leaving less productive firms operate only in domestic market , and simultaneously force the least productive firms to cease producing.

The self-selection hypothesis has been exposed to empirical tests in a number of studies. The major results are summarised in Table A . The previous studies cover a number of developed and developing countries in Europe(UK,Spain,Italy) , America (US, Mexico,Colombia), Asia(China, Korea) and Africa(Morocco) . Both cross section and panel data methodologies are employed to reveal the determinants of export decision. Generally speaking, most empirical studies on self-selection indicate that sunk entry costs are important for the export decision and find evidence supporting the hypothesis that more productive producers self-select into export markets. The underlying empirical framework and methodologies employed are consistent across studies.

On the other hand,there exist plausible reasons to believe that exporting can improve technology efficiency, which is crucial to productivity. The channels through which firms can obtain post entry productivity gains include fiecer competition in foreign markets and learning from their international buyers. International buyers who always want low-cost , better quality products may transmit knowledge from other suppliers to the exporting firms (World Bank 1993). Moreover, firms which are struggling to remain in the foreign market , once entered, will be motivated to learn the new production methods, inputs and designs from their competitors to keep up with the technology efficiency frontier.

This “ learning by exporting” argument is supported by industry studies that document the knowledge flows from foreign buyers to exporting firms and technology spillovers in international markets. (Mckinsey report 1993 , World Bank 1993, Rhee,Ross-Larson and Pursell 1984). The empirical implication of this view focuses on post-entry performance. With learning by exporting, firms that enter and stay in the export market should enjoy faster productivity growth and higher productivity levels than their domestic counterparts after entry . Apparently, this will lead to a significant productivity gap between exporters and non-exporters in a cross section investigation.

The main results of empirical work on learning effects are summarised in table B (adapted from Girma , Greenaway and Kneller 2002 with a few additions).Compared to self-selection , the methodologies used to investigate learning hypothesis are diversified and the results are inconclusive. As illustrated in table B , the learning effect is supported in five economies (Taiwan, Mainland China, Morocco, UK and Italy) but receives no support in the other five (US, Korea, Spain, Colombia and Mexico). The methodologies employed to test the learning effect differ from study to study, due to a lack of clear theoretical model and consistent empirical framework. Almost every single study employs a somewhat different approach to reveal the causality from exporting to productivity, which depends on the quality of available datasets. However, there is a common feature among the studies using panel data. Current level or growth rate of productivity performance is regressed on past exporting experience controlling for firm characteristics and a set of industry ,region and time dummies , although the specifications and measures of productivity performance vary across studies.

Table A Summary of key features of empirical studies on self-selection

Author	Region	Sample	Methodology	Main results
Aw , Chung and Roberts (1995b)	Taiwan Korea	88,000-100,000 firms in 1981,1986 and 1991 39,022-88864 firms in 1983,1988,1993	Cross section	Ex-ante higher productivity of exporters Support for Self-selection
Roberts and Tybout (1997)	Colombia	All plants in 19 industries 1981-1989	ML technique with MSM Panel data	Importance for Entry cost and sunk-cost hysteresis in exporting
Bernard and Wagner (1997)	German	7624 firms 1978-1992	Panel data	Self-selection of exporter
Cleridas Roberts and Tybout (1998)	Morocoo Mexico Colombia	All plants 1981-1991 2800 firms 1986-1990 All firms 1984-1991	FIML and GMM on cost function Panel data	Evidence for self-selection Reduction in AVC increase the probability of exporting
Bernard and Jensen (1999)	U.S	50,000-60,000 plants 1984-1992	Linear Probability with fixed effects	Ex-ante success of exporters Evidence of Self-selection
Bernard and Jensen (2001)	U.S	13550 plants 1984-1992	Linear Probability with and without fixed effects	Importance of entry cost and plant heterogeneity in export decision No geographic and industry spillover No noticeable effect of subsidy on exporting
Delgado, Farinos and Ruano (2001)	Spain	1,766 firms 1991-1996	Non-parametric analysis of productivity distribution	Higher productivity of exporters Self-selection of exporting firms
Girma, Greenaway and Kneller (2002)	UK	8,992 firms	Probit regression	Self-selection of exporters in terms of productivity Inverse U shape between export intensity and export probability

Table B A summary of empirical studies on learning by exporting

Author	Country	Sample	Methodology	Main results
Aw , Chung and Roberts (1995)	Taiwan (China) Korea	88,000-100,000 firms in 1981,1986 and 1991 39,022-88864 firms in 1983,1988,1993	Cross section	Taiwan : Productivity improvements after entry in 3 industries Korea : no significant productivity changes following entry or exit Inclusive evidence for learning by exporting
Cleridas, Roberts and Tybout (1997)	Morocoo Mexico Colombia	All plants 1981-1991 2800 firms 1986-1990 All firms 1984-1991	FIML and GMM on cost function Panel data	No learning in Colombia and Mexico Some learning in Morocco
Kraay (1999)	Mainland China	2105 firms 1988-1992	Dynamic Panel	Learning from exporting for established exporters Insignificant learning effect for new entrants
Bernard and Jensen(1999)	U.S	50,000-60,000 plants 1984-1992	Panel data	No evidence of learning effect
Delgado, Farinos and Ruano (2001)	Spain	1,766 firms 1991-1996	Non-parametric analysis of productivity distribution	Inclusive evidence on learning from exporting
Castellini (2001)	Italy	2,892 firms 1989-1992	Cross section	Learning associated from exporting
Girma, Greenaway and Kneller (2002)	UK	1387 new entrants and 781 mactching frims	Matching technique Difference in difference	Evidence for learning by exporting Productivity of entrants grow faster than the mactching firms in the first two year after entry

3 Chemical Industry

Data

The data set used in this paper is a subset of the UK manufacturing firm level panel data from Onesource database[1]. This dataset contains information on 461 companies in UK chemical sector over the period 1989 to 1999, yielding 2,883 observations. There are 6 years of observations for each company. The data set include 5-digit ISC code, year, total employment , real turnover , real wage, real exports , real fixed assets and real value added for each firm. All the real values are deflated by disaggregated price deflators. Firm-level productivity is measured by TFP(total factor productivity), labour productivity and AVC(Average variable cost). We generate firm level TFP index as residuals from three factor constant return Cobb-Douglas regression. Labour productivity is measured as gross real output per worker, while AVC is measured as the labour and material cost divided by real sales.

Characteristics of chemical industry

According to DTI (department of trade and industry) and CIA (chemical industry association) ,the UK chemical industry is the country's largest manufacturing sector. It employs more than 400,000 people throughout the country ,producing and selling a diverse range of materials and products worth over £40 billion annually, accounting for 13% of the value added by the whole of the UK manufacturing industry. It is also UK's number one exporter , with exports of 25.8 billion and a trade balance surplus of 4.6 billion in 2000.(see figure 1)

The UK chemical industry is highly research based and technologically advanced, with significant expenditure on research and development(DTI ,2003). In 1997, R&D expenditure, at 2.8 billion, was up to 8.7% of the whole sales, which is almost six times as high as in other manufacturing.(see figure 2). From 1990 to 2000, productivity measured by output per worker has risen by more than 5% annually (see figure 3) and its annual output growth rate achieved 3% , which is five times as high as the average manufacturing growth rate and the second highest among all manufacturing sectors.

Exporters versus non-exporters

Figure 4 presents the shares of exporters and non exporter in total firm number, total output and employment from 1989 to 1999.It can be seen clearly from this figure that the export group did not exceed the non-exporter group in terms of all the three indicators until 1996. In the starting year 1989, non-exporters as a whole dominated this industry. More than eighty percent of all the firms were non exporters in that year, which produced more than eighty percent of total outputs and employed more than eighty percent of all the workers. Exporters only consists a small proportion of this sector: their share of firm numbers, outputs and employment are all below 20

[1] For the description of the original dataset, please refer to Sourafel Girma, David Greenaway, Tichard Kneller (2001) , pp 5

percents. However, the differences between the exporter group and the non exporter group became smaller after 1990. In 1990 , exporter's share of firm number jumped up to 35.75% and then rises up to 45% in 1996 , though their shares of firm numbers , total outputs and total employment are still less than those of non-exporters. Nonetheless, this pattern is reversed since the turning-point year 1997. From 1997 to 1999, exporters outweigh non-exporters in terms of all the three indicators . Exporters' shares of firm number ,total output and total employment rise up to 50-60% , whereas those of non exporters declined to 40-50%. Moreover, exporters account for a somewhat smaller share of gross output and employment than their share of firm numbers, which implies that the average size of exporters are *smaller* than non-exporters.

Table 1 compares the average performance differential between exporters and non-exporters in chemical industry with those of all other manufactures. On average , exporters in chemical industry are *smaller* , but more efficient and pay higher wages than non-exporters. They produce 10% less outputs, gain 13% less value added , and employ 14% less than non-exporters on average, though average wage of workers in exporting firms are still 7.6% higher than those working in domestic producers. However, exporters 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 the industry mean, so the gap between the mean TFP of exporters and non-exporters is 7.9% , relative to the industry mean. On the other hand, for all other manufactures, exporters are also more productive and pay higher wages, but are *larger* than non-exporters. They produce 10% more outputs , gain 10.6% more value added and employ 11% more workers and pay 1.5% higher than non-exporters. The mean level of labour productivity and TFP of exporters are 3.5% and 6.4% higher than non-exporters, respectively.

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Table 1 Average performance of exporters and non-exporters.

Variables	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 presents the persistence of firm's export status over ample period.As to the pattern of switching export status, in chemical sector, 90.83% exporters continue to export and 95.55% non-exporters continue to operate only in domestic market. On the other hand, only 4.5 percent of current exporters quit and only 9 percent of current non-exporters enter at the next period. So the behaviour of exporting or not exporting is persistent over time. The persistence of exporting status indicates the importance of sunk entry cost , as suggested by Robert and Tybout (1996). This pattern is similar in all other manufactures , but the probability of entering and quitting are higher than those in automotive sector.

Table 2 Transition matrix of 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

The results of exporters' superior productivity performance and the persistence of firm's export status are consistent with the findings in the previous studies. However, the result that exporters on average have less gross revenue and employment than non-exporters is striking, especially combined with the fact that exporters are substantially more efficient. If , as new trade theory suggests, scale economy is playing an major role in determining intra-industry trade, then exporters tend to be both larger and more productive than their purely domestic firms because of their extra revenues from over sea markets. Berry(1992) also summarises that exporters of manufactured goods come from relatively larger firms . However the fact that exporters are smaller in our study may imply that in UK chemical industry ,scale economies can neither be the reason for firms' decision to export , nor explain exporter's superior productivity performance.

4 **Empirical model**

Export Premia

The specification used to estimate the the export premia is :

$$Y_{it}=\alpha E_{it}+D_{tj}+\varepsilon_{it} \qquad [1]$$

where Y_{it} denotes firm performance such as log of employment, log of real sales, log of value added , and measure of productivity level. D_{tj} is time and industry dummies .Note that ε_{it} is assumed to be a well-behaved zero-mean disturbance term without considering the plant effects of the panel data. The coefficient α then indicates the export premia in terms of different firm performance.

Test for Self-selection

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 :

$$Y_{it} = \begin{cases} 1, & \text{if } \alpha \mathbf{Z}_{it}+ FY_{it-1} - F+\varepsilon_{it} \geq 0 \\ 0, & \text{otherwise} \end{cases} \qquad [2]$$

where Y_{it}, Y_{it-1} , F and $\mathbf{Z}_{it}$ denote current exporting status, lagged exporting status , sunk export fixed cost and plant characteristics. However, econometric estimation of [2] is problematic. The key issue is our assumption about the disturbance term ε_{it}. The simplest approach is to take ε_{it} as independent standard normal variables. If so , then the panel nature of the data is irrelevant and the standard Probit or logit model would apply(Greene ,2000, pp813-836). 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 ε_{it} as composed of unobserved plant effects , μ_i , plus transitory term η_{it}. Apparently , if $\varepsilon_{it} = \mu_i + \eta_{it}$, then the standard Probit regression is inappropriate . The new problem is whether the plant effect μ_i is random or fixed. If μ_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, p829). The alternative approach is to use linear probability model with fixed effects. Therefore, three different approaches can be applied to test self-selection hypothesis, each of which is based on alternative assumptions of plant effect. In previous studies, Probit regression is employed in Girma, Greenway and Kenller (2002) , 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.

In this paper , we will employ the the linear probability approach in Bernard and Jensen(1997,2001) , and use probit regession approach as a robustness check. Bernard and Jensen(2001,pp12) has pointed out that in export decision model, there are plausible reasons to adopt fixed rather than random effect approach . Firstly, random effect specification requires that the random effects be uncorrelated with regressors, but in our model the unobservable plant effects such as managerial ability and technology are likely to be correlated with observable plant characteristics such as employment , wage and productivity. Secondly, since the time dimension of the panel is long (11years), the bias induced by fixed effect estimators might be ignored.

The linear probability model employed in this paper is as follows:

$$Y_{it}=\alpha\ln(Employ_{it-1})+\gamma\ln(Wage_{it-1})+\chi Productivity_{it-1}+\theta Y_{it-1}+D_{tj}+\varepsilon_{it} \quad [3]$$

Where employment, wage are used as proxy of firm size and human capital. D_{tj} is the control for time and industry dummy.

As discussed previously, the linear probability model with fixed effect is :

$$Y_{it}=\alpha\ln(Employ_{it-1})+\gamma\ln(Wage_{it-1})+\chi Productivity_{it-1}+\theta Y_{it-1}+D_{tj}+\mu_i+\eta_{it} \quad [4]$$

To avoid the inconsistent estimators found in the fixed effects (Bernard and Jensen, 2001,p.12), the first difference form of [3] is estimated :

$$\Delta Y_{it}=\alpha\Delta\ln(Employ_{it-1})+\gamma\Delta\ln(Wage_{it-1})+\chi\Delta Productivity_{it-1}+\theta\Delta Y_{it-1}+\Delta\eta_{it} \quad [5]$$

Second and third order of the lags of the levels of the explanatory variables , $Employ_{it-2,-3}$, $Wage_{it-2,-3}$, $Productivity_{it-2,-3}$ and $Y_{it-2,-3}$,are used as instrumental variables for $\Delta Employ_{it-1}$, $\Delta Wage_{it-1}$, $\Delta Productivity_{it-1}$and ΔY_{it-1}.

In this paper, We will focus on the IV-first difference linear probability model specified in Eq[5], and also conduct probit regression as an alternative approach for robustness check.

Test for Learning by exporting

The simplest idea to test whether exporting can boost exporting productivity is to regress current productivity performance on past exporting status. In previous studies, a number of different approaches from GMM (Clerides,Lach and Tybout 1998) to matching technique (Girma, Greenaway and Kneller 2002) have been applied . In this paper, we will employ the approach used by Kraay (1999) to investigate the effect of first order lagged exporting status on current productivity level.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. For example, if firms self-select into export market and the positive productivity shock is serially correlated, current productivity will also be correlated with previous export experience without learning by exporting.

To rule out the above two alternative explanations, the specification used in this paper, following the methodology of Kraay(1997), is :

$$Y_{it}=\alpha Y_{it-1}+\chi E_{it-1}+\mu_i+\eta_t+\varepsilon_{it} \qquad [6]$$

Where Y , E denotes productivity performance and exporting status dummy ,respectively. μ_i and η_t are firm specific and time-specific effects, ε_{it} is then a well-behaved zero mean disturbance , which is assumed to be independent of E_{it-1} and not serially correlated. The lagged productivity $Y_{it-1}$is included as explanatory variable in order to eliminates the effect of serial dependence in productivity. To get consistent estimators of α, χ in the presence of μ_i and η_t , the following strategy is used: Firstly, take deviation of Y and E from period means to get Y^*_{it} , Y^*_{it-1} and E^*_{it-1}, that is , retrieve the residuals from the regression of Y and E on a set of time dummies. Secondly , take first differences of Y^*_{it} , Y^*_{it-1} and X^*_{it-1} use the specification:

$$\Delta Y^*_{it} = \alpha \Delta Y^*_{it-1} + \chi \Delta E^*_{it-1} + \Delta \varepsilon_{it}{}^* \qquad [7]$$

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 ΔY^*_{it-1} and ΔE^*_{it-1}.

Regression [6] and [7] can be used to reveal the relationship between lagged export status and current firm performance. The coefficient of lagged export status χ in

Eq.[7] measures the effect of first order lagged exports on current productivity level resulted from learning by exporting . However, Kraay(1999) argued that there are compelling reasons to believe that the learning effect may depend on the export history of a firm. That is , the magnitude and significance of χ may vary across groups with different past export experiences . For example, if learning by exporting is an once-off effect which only occurs in the first few years after a firm breaks into the export market , then χ should be positive and significant among new entrants , but negative or insignificant for firms which has already been exporting continuously for many years. Therefore, it seems to be necessary to control for export history in estimation Eq.[8] and [9].In this paper, we consider three different groups with different export history: established exporters , entrants and compare their performance with non-exporters. So five types of firms , as shown in the following table, are considered while other firms such as exiters and switchers are excluded.

Group	**Export history**	Export status prior to period t -4	Export status at t -3	Export status at t -2	Export status at t -1
1	**Established exporters**	Firms exporting at each period over the sample period			
2	**Entrant_3**	**0**	**1**	**1**	**1**
3	**Entrant_2**	**0**	**0**	**1**	**1**
4	**New entrants**	**0**	**0**	**0**	**1**
5	**Non exporters**	Firms which have never exported in the reported years			

For i^{th} firm at time t , group 1 include established exporters which started exporting before the sample period and remain exporting over the entire sample period; group 2 ,3 and 4 represent entrants which breaks into the export market three years , two years and one year prior to the current period , respectively. Group 5 are the firms that have never exported in the panel.

To investigate how the learning effect vary with firms with different export histories (from group 1 to group 5) ,[7] is modified to allow the coefficients on lagged exports vary with the different types of the firm.

$$Y_{it}=\alpha Y_{it-1}+[\chi^1 \cdot D^1 + \chi^2 \cdot D^2+\chi^3 \cdot D^3+\chi^4 \cdot D^4]E_{it-1} +\mu_i +\eta_t + \varepsilon_{it} \qquad [8]$$

Where the dummy variable D^i takes the value 1 if the firm is in group i , (i=1,2,3,4). So χi (i=1,2,3,4)is the coefficient on lagged export status for firms in group 1 to group 4. By comparing $\chi 1$ to $\chi 4$, one can find how learning effect vary across firms with different export experience.The same transformation as before can be applied to Eq.[9]. That is , first take deviations of Y and E from time specific means and then take first difference to eliminate firm-specific effect. So the following estimation can be used:

$$\Delta Y^*_{it} =\alpha \cdot \Delta Y^*_{it} +[\chi^1 \cdot D^1 + \chi^2 \cdot D^2+\chi^3 \cdot D^3+\chi^4 \cdot D^4] \Delta E^*_{it-1} + \Delta\varepsilon_{it}{}^* \quad [9]$$

where second and higher order lags of $Y(Y_{it-2}\ Y_{it-3})$ and E interacted with D^j (D^j E_{it-2}, D^j E_{it-3} ,j=1,2,3,4)are used as instruments.

5 Empirical Results and Analysis

Export Premia

The results are reported in table 3. For firms in all manufacturing sectors , the results replicate those reported by Girma, Greenaway and Kneller(2002). Exporters are larger, more efficient and pay higher wage on margin. However, the pattern of export premia in chemical sector differs from other manufactures in two respects. Firstly, There is no evidence that exporters are significantly larger than non-exporters in chemical industry. Output and value added level in exporting firms are a bit higher than non-exporters, but the gap is statistically insignificant, while exporter's employment is 3.7%lower than non-exporters and again statistically insignificant. Secondly, the productivity differentials in 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 (7% controlling for capital intensity) 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. These findings are consistent with the average performance differential results reported in section 3. Generally speaking, in chemical industry exporting firms are more productive and no larger than their domestic counterparts, and the export premia in productivity is greater than all other manufactures.

Table 3 Export premier

Variables	Other manufactures	Chemical
Sales	0.403***	0.00565
Employment	0.321***	-0.037
Wage	0.0446***	0.0643***
Value added	0.283***	0.008
AVC	-0.0146**	-.020**
Labour productivity	0.0756***	0.104***
TFP	0.074***	0.091**

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

Self-selection

Table 4 reports the results from Eq.[5] , as well as from probit regression using the same regressors. Since the results are similar for alternative productivity measures, for brevity, we only report the results using TFP as measure of productivity.

Column 1 of table 3 reports the coefficients of plant characteristics and lagged exporting status from the first difference linear probability model. In the linear probability model, employment and sales is negatively and insignificantly correlated with probability of exporting, 1% increase in employment and sales lower the probability of exporting by 12% and 19% respectively , and insignificant in conventional levels. However, TFP is positively and significantly correlated to exporting probability. For a 1% increase in TFP the probability of exporting increases by 6.8% and significant at 5% level. Previous exporting status remains to be a powerful predictor, exporting at previous period increases the probability of exporting by 69.1%. Results from a probit model confirms the results from first difference linear probability specification. So the pattern of determinant of exporting in chemical sector is (a) More productive firms are more likely to participate in the exporting market. Self-selection hypothesis is strongly supported . (b) As expected, hysteresis effect is also large, which confirms the persistence of export status over time as a result of sunk export entry cost. (c) Size is less important in exporting decision than productivity. There is *no* evidence that larger firms are more likely to be exporting.

Table 4 The determinant of exporting : Chemical sector

Dependent variable: Exporting Status

Approach	Linear Probability (First difference IV)	Probit
Sales	0.0032 (0.24)	0.0172 (0.48)
Employment	-0.11964 (-0.65)	-.0265* (-1.83)
Wage	-0.1885 (-1.06)	- .0338337 (-0.61)
TFP	0.068** (2.19)	0.294** (2.94)
Previous exporting status	0.691*** (76.23)	0.867*** (82.6)

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

Learning By Exporting

The tests for learning effect are reported in table 5 and table 6. Table 5 represents estimation results from Eq.[7].When TFP and labour productivity are used as dependant variables, the coefficient of lagged exporting regressor is positive and significant at 10% level, which implies that there is statistically significant evidence of learning by exporting. The magnitude of learning effect is large. Exporting at current period leads to an impressively 9 percent increase in total factor productivity and 13 percent increase in labour productivity in the next period. The P-value for serial correlation show that the non-serial-correlation assumption is valid for TFP and labour productivity. The coefficient of lagged exporting is also positive when productivity is measured by AVC , which implies a negative effect of previous exporting on current productivity. But as pointed out by Clerides Lach and Tybout(2002), since average variable cost does not include capital cost, learning effect might be missed if the exporting firms are more labour intensive and efficiency gains are captured by workers as higher wages if productivity is measured by AVC. On the other hand, the P-value for AVC rejects the null hypothesis that there is no serial correlation , which violated our previous assumption about $\varepsilon_{it.}$ So the dynamic panel instrument methodology is not a perfect approach when productivity is measured by AVC. Therefore , in short, the above results show that exporting in the last period has a positive effect on current productivity level , implying that the learning-by-exporting is well supported.

Table 5 : **Learning effect in Chemical sector**

Dependent Variable : Productivity

Measure of Productivity	TFP	Labour productivity	AVC
Lagged Productivity	0.367*** (3.46)	0.205 (1.06)	0.0201 (0.21)
Lagged exporting status	.0955* (1.83)	0.131* (1.85)	0.0251 (0.51)
P-value for serial correlation▲	0.87	0.21	0.011**

The results of estimation [9] are reported in Table 6.In contrast to Kraay(1997) , We find that learning effects are positive for entrants but negative for established exporters. For new entrants which have never exported before , exporting at entry year can raise productivity level of the next year by 5.7 percent. However, for established exporters, current productivity level is negatively correlated with lagged exporting. The coefficients are significant at 5% level for both new entrants and established exporters. Therefore, there are plausible reasons to believe that learning effect are more pronounced among new entrants rather than established exporters. Moreover, for firms which enter the export market at three or two years prior to the current period, lagged exporting leads to an improvement in current productivity level by 2.5% and 0.6% , respectively. This indicates that , though there still exits positive learning effect, “earlier” entrants enjoy less productivity gains from lagged exporting than new entrants. Therefore, it seems that learning effect become smaller and less significant when a firm’s exporting experience is increasing.

Table 6 : **Learning effect controlling for export history**[1]

Sector	Chemical
Established exporters	-.00415 ** (2.45)
Entrant _3	0.0069 (0.68)
Entrant _2	0.025* (1.36)
New entrants	0.057** (3.14)

The above results show that exporting firms with less past exporting experience tend to benefit more through learning by exporting, and there is no evidence of learning effect for exporters which have already been exporting continuously for many years . Since established exporters are those firms which have successfully survived through the fierce competition of export market for many years, they should have already exhausted the benefit from learning and achieved optimistic productivity level in order to cope with the intensive global competence. Therefore, lagged exporting is not likely to have positive effect on current productivity for established exporters. On the other hand, new entrants are those who have never been exposed to global demand and competition. So they are more likely to take advantage of the contact with international best practice, and learn from their clients and competitors to boost their productivity.

5 Conclusion

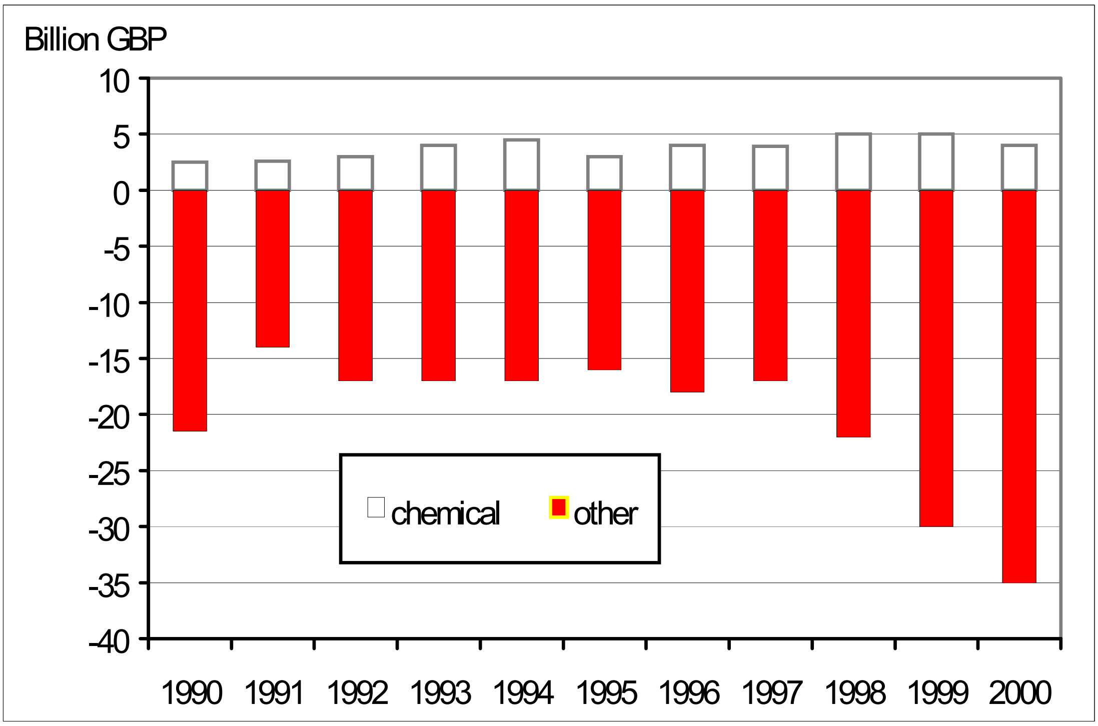
In this paper, we consider the causal link between export and productivity at firm level in a highly technology intensive UK industry which is a large exporter and has experienced high productivity growth rate during the last decade. We find the fact that although contrast to all other manufactures exporters in chemical industry are no larger than than non-exporters, they are more efficient than their purely domestic counterparts. Moreover, the productivity differential between exporters and non-exporters is greater than those in all other manufactures. Previous studies have provided two different but not mutually exclusive mechanisms to explain the superior productivity performance of exporters : the self-selection and learning-by-exporting mechanism. Our study find strong support for both of them. Firstly, in both linear probability model and probit model , increase in total factor productivity level significantly increase the probability of exporting. On the other hand, the association between lagged export and current productivity is positive and significant. These results are consistent with the self-selection and learning by exporting models. Moreover, in contrast to Kraay(1999) ,we find the learning-by-exporting effect is diminishing as firm's past export experience increases. The learning effect is the

[1] Productivity is measured by TFP. The results of labour productivity and AVC follow are similar so not presented here for brevity.

greatest among new entrants, smaller but still positive for earlier entrants, and negative for established exporters.

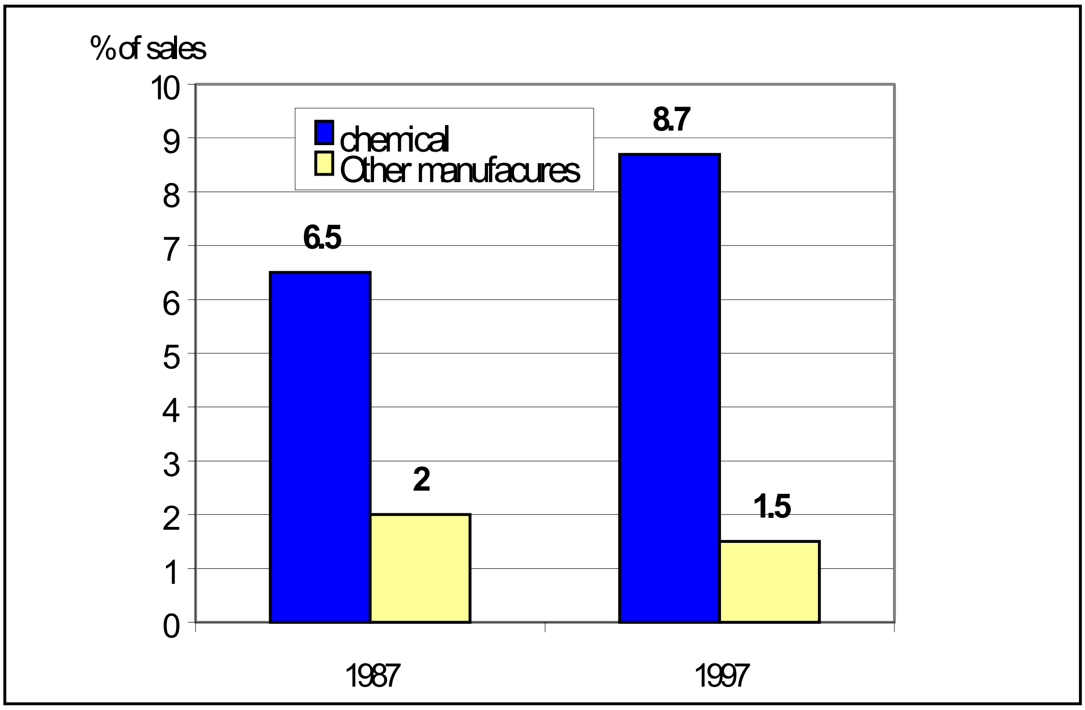
These results raise further questions for future research. For example, can the presence of learning forces be linked to specific industry characteristics such as technology intensity and export intensity? Our study shows that in chemical industry, the UK's number one exporter and highly technology intensive sector, though exporters are no larger then non-exporters , the productivity differential between them is positive and greater than all other manufacture sectors , which may be explained by the combination of self-selection and learning-by-exporting effects. Are the benefits of learning forces more likely to accrue to firms in more technology intensive and export intensive industries? Why exporters are marginally no larger , on average smaller but still more productive than non-exporters in UK's chemical industry? Further research may be directed to investigate whether learning-by-exporting forces can be determined and explained by cross-industry effects and the underlying link between them.

Figure1 UK trade balance in chemicals and all other manufactures



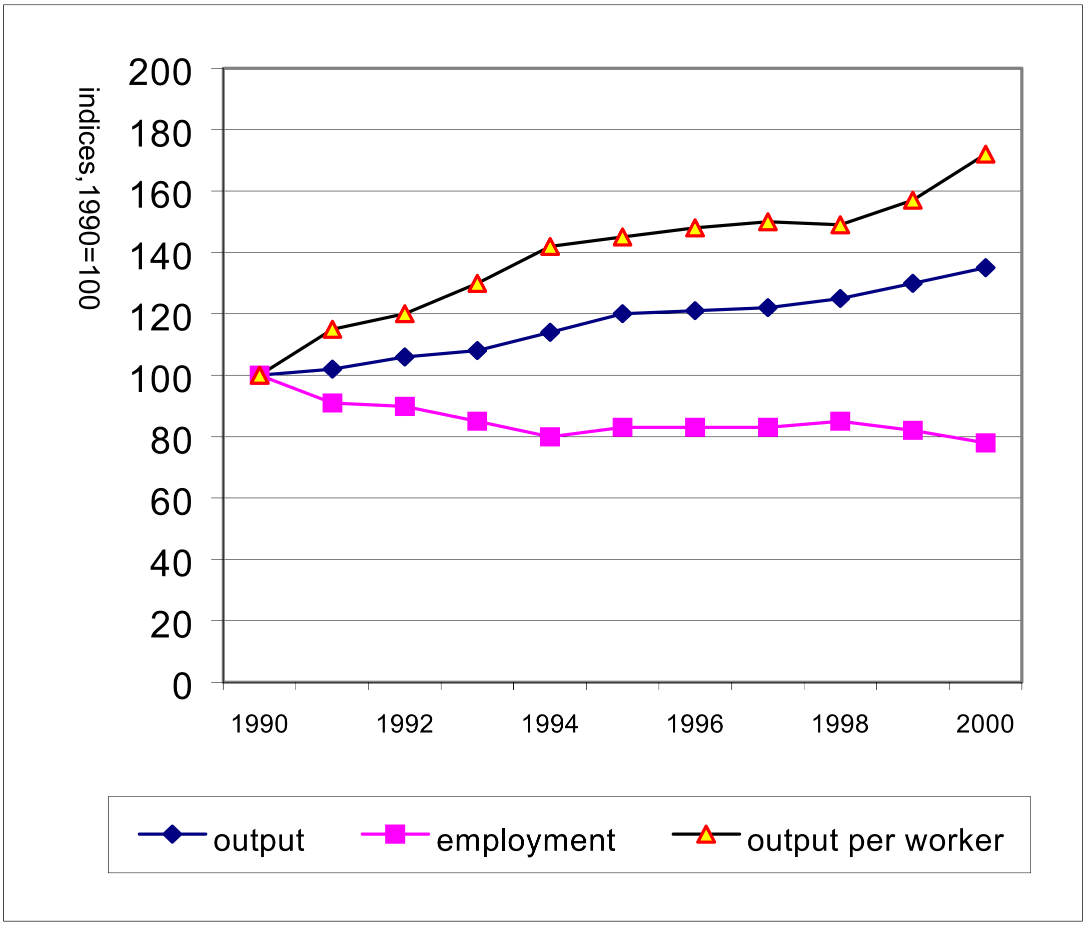
Source : UK chemical Industry association , www.chemical-industry.org.uk

Figure 2 UK manufacturing R&D expenditure



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

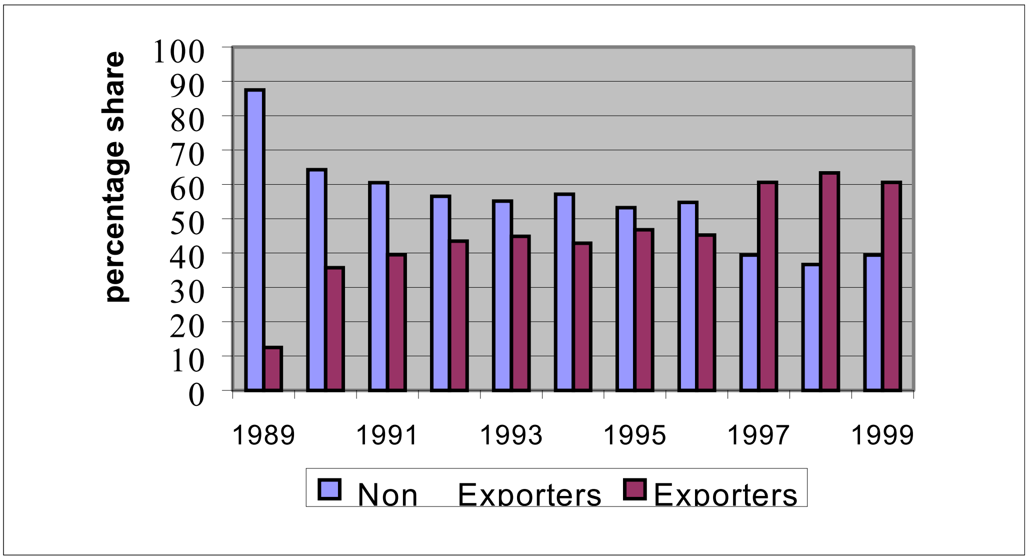
Figure 3 UK chemical industry employment, output



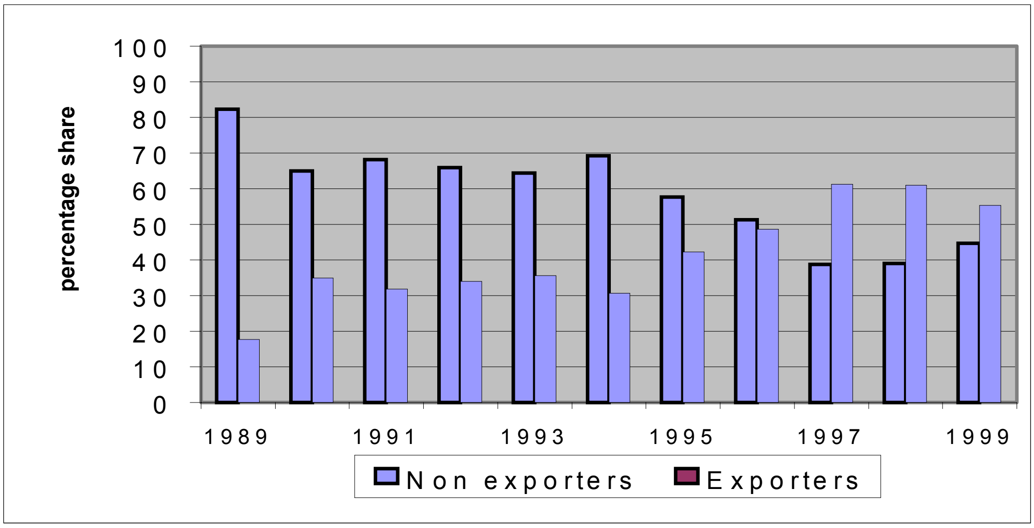
Source : UK chemical Industry association , www.chemical-industry.org.uk

Figure 4 Shares of exporters and non exporters in Chemical Sector

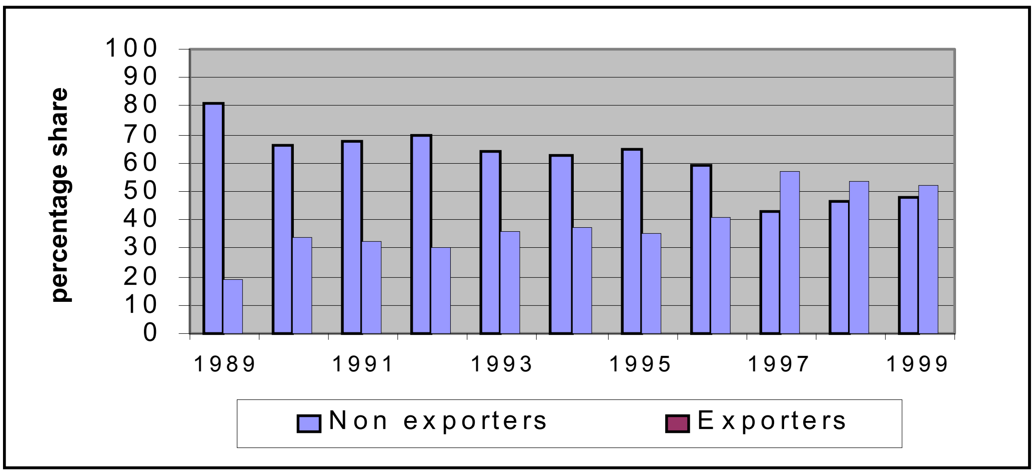
Panel 1 : Share of firm number : Exporters VS. Non exporters



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



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



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