# Productivity, Exporting and the Learning-by-Exporting Hypothesis: Direct Evidence from UK Firms*

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JEL classification: F12, L1

Keywords: Productivity, Exporting, Learning.

October 2006, revised April 2007

**Abstract**

Case studies suggest exporters learn from clients. Econometric evidence is mixed. We use firm-level panel data on exporting and productivity with direct information on learning sources, including clients. We find: (a) firms who exported in the past are likely to learn more from clients (relative to other sources); (b) firms who learned from clients in the past are more likely to have faster productivity growth; (c) the reverse is not the case i.e. past productivity growth is not associated with more learning from clients and past learning from clients is not associated with more exporting. These results are consistent with the learning-by-exporting hypothesis.

## 1 Introduction

There is a growing theoretical and empirical literature on the relation between firm productivity and exporting. Understanding the mechanisms underlying this relationship is a very important policy issue; many governments have, for example, export-supporting subsidies. An efficiency-based justification could be if firms improve their technology via learning from their export customers and this generates a spillover that raises productivity.

Most work that examines the "learning-by-exporting" hypothesis looks at the relation between exporting and (subsequent) productivity growth, with mixed findings.[1] One problem with this work is that it is rather indirect. If exporting does affect learning, and learning then affects productivity growth, it would be valuable to test this *directly* using data on exporting, learning and productivity growth. Since learning is a difficult variable to measure, almost all studies are forced to study the relation between exporting and productivity growth. This might obscure the learning/exporting relation if there are other unmeasured variables that affect productivity growth and are correlated with exporting.

Our paper therefore differs from other work since our data contain information on productivity, exporting and, most crucially, learning for a panel of UK firms. For each firm we have information on productivity and exporting. For learning, firms are also asked to report the sources of knowledge for any innovation they have carried out. One of those sources of knowledge is "clients or customers" (others are "suppliers", "within the firm", "consultants", "competitors" etc.). We also know whether the firms export or not. Thus our test of the learning-by-exporting hypothesis is as follows. First, we examine whether firms who export are then more likely to report learning from customers (relative to the other types of learning they specify). Second, we examine whether such learning is related to later productivity growth.

Our data are not of course perfectly suited to testing this hypothesis: the question is about learning from all buyers, not necessarily from domestic or foreign and we can only measure labour productivity growth. But we do find what we think are interesting correlations on these data that seem to be robust to e.g. unobserved firm fixed effects and the like. After checking our data against other results on exporting and productivity,[2] we find the following. First, firms who had exported two years previously report more learning from clients (relative to other sources of learning). This holds in the cross section and controlling for fixed effects, so that firms who had changed their exporting status report significant changes in learning from customers.

Second, interestingly we also find that firms who had exported previously report *no* significant changes in learning from any of the *other* sources of knowledge that we have data on e.g. suppliers, within the firm etc (again holding in the cross-section and controlling for fixed effects). Thus there does seem to be a relation between exporting and subsequent learning from clients, but not between exporting and subsequent learning from other knowledge sources.

Third, we find that firms who have had an increase in learning from customers have higher subsequent productivity growth. Fourth, we find no evidence of timing in reverse. There is no statistically significant relationship between past productivity growth and subsequent learning from customers and between past learning from customers and subsequent exporting.

Together, these four results suggest that that learning from clients is associated with future labour productivity growth. In addition learning from clients is strongly associated with previous exporting, consistent with learning from clients arising via exporting. The reverse relationship – i.e. increased learning following higher productivity growth – does not hold. A possible explanation of why our results in favour of the learning-by-exporting hypothesis might be stronger than those found in most of the previous exporting-productivity studies is that the impact of learning effects might have been hidden by the noise in productivity measures when direct learning measures were not available.

How does our study relate to other work that uses direct learning data? MacGarvie (2006) is, to the best of our knowledge, one of the few papers that uses direct learning data, in her case patent citations. She finds that French firms who export do not cite significantly more patents from their destination countries. She conjectures, however, that firms might learn from foreign customers in ways that are not captured by patent citations. Baldwin and Gu (2004), for Canadian firms, use as indicators of learning-by-exporting R&D cooperation with foreign buyers; foreign sourcing of advanced technology in the plant; and (lack of) information on foreign technology. They find positive correlations of all these variables with exporting and with productivity growth.[3]

The rest of the paper proceeds as follows. Section 2 describes our approach, Section 3 describes our data, Section 4 reports the results and Section 5 concludes.

## 2 Estimation Strategy

We set out below a simple framework. Our purpose here is not to describe precisely what others do but to try to explain the issues at hand and where our contribution, we think, is.

We follow the extant literature and assume that firms have a constant-returns log linear Cobb-Douglas output production function $Y = AK^{\beta}N^{1-\beta}$, where Y is output, K is physical capital, N is employment and A is the knowledge stock at the firm. Many papers have estimated an augmented productivity growth equation:

$$\Delta \ln(Y/N)_{i(t,t-\tau)} = \alpha_1 EXPORT_{i(t-\tau)} + \beta \Delta \ln(K/N)_{i(t,t-\tau)} + \sum_k \alpha_k Z_3 + \varepsilon_{it} \qquad (1)$$

where (labour) productivity growth - $\Delta \ln(Y/N)$ - of firm i between $t$ and $t$-$\tau$ depends on growth in capital intensity, $\Delta \ln(K/N)$ over the same period, on a vector of other time varying and time invariant factors $Z_3$ (e.g. size, location, industry, ownership status) and on export status at the beginning of the period ($EXPORT_{t-\tau}$), τ here and below denotes time and the error term $\varepsilon_{it}$ captures other unobserved factors that affect labour productivity growth and/or measurement error. The literature has been particularly interested in the coefficient on EXPORT. The rationale behind this specification is that firms learn by exporting and learning leads to productivity growth. Most of the existing papers could only estimate variants of this reduced form because of the lack of direct information on learning, in particular from customers.[4]

In this paper we have direct measures of learning. Thus, we can proceed in two stages. First we see if learning from customers is correlated with exports (we also look at learning from other sources). Specifically, we can estimate whether exporting at time t-2 affects how much firms learn from customers over the period t-2 and t ($LEARN^{CUSTOMERS}$):

$$LEARN^{CUSTOMERS}_{i(t,t-\tau)} = \delta_{1j} EXPORT_{it-\tau} + \sum_k \delta_{j,k} Z_2 + v_{it} \qquad (2)$$

where *EXPORT* denotes the export status of the firm, $Z_2$ is a vector of characteristics that also affect $LEARN^{CUSTOMERS}$ and $v_{it}$ is an error term that captures unobserved characteristics and/or measurement errors and/or idiosyncratic shocks, and again for simplicity we have assumed linearity.

Our second stage is to see if learning leads to growth in the knowledge stock, ΔlnA, (this is captured formally for example in the knowledge production function, Griliches, 1979). Thus, in this framework and given the data at hand we can test this by estimating:

$$\Delta \ln(Y/N)_{i(t,t-\tau)} = \sum_j \gamma_j LEARN^{CUSTOMERS}_{i(t,t-\tau)} + \sum_k \gamma_k Z_4 + u_{it} \qquad (3)$$

where $Z_4$ is a vector of characteristics depending on data availability, to see if LEARN over the period t and t-τ (which we shall find is correlated with EXPORT) is correlated with $\Delta\ln(Y/N)_{i(t,t-\tau)}$.

We do not deal with the determinants of exporting. The implications this has for empirical work are set out in Clerides, Lach and Tybout (1998), see especially section 2. Suppose first that all firms have the same productivity and exporting is randomly determined, after which learning does or does not take place. Regressions like (1) (perhaps with exporting lagged) would be a sensible first step at examining learning-by-exporting. Suppose however, as Clerides et al (1998) do, that only higher productivity firms export (and subsequently learn). Thus in the period before exporting firms productivity rises until they are productive enough to export, and then in the period after exporting firms productivity rises as they learn. Even if learning-by-exporting is true then, without further restrictions on these two processes it is not possible to say whether productivity growth rises or falls after exporting. All this suggests the potential use of direct learning data. It also suggests examining the reverse timing of that set out in equations (2) and (3), namely past learning from clients on subsequent exporting and past productivity growth on subsequent learning.

We implement this below. Finally, we note that we have no natural experiment in the data and our identification strategy relies on fixed effects and lags.

## 3 Data

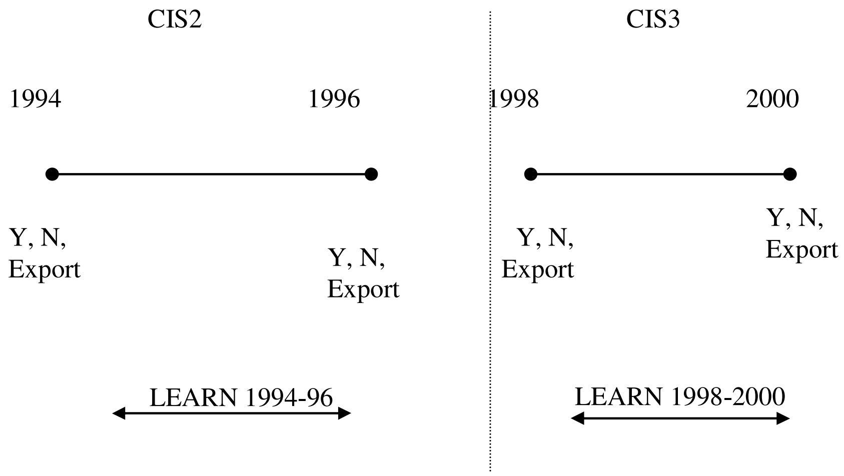
### *3.1 Data set*

The U.K. Community Innovation Survey (CIS) is based on a common EU-wide survey of innovation outputs; innovation inputs and sources of knowledge for innovation. The three existing waves of U.K. CIS surveys were CIS1 (covering 1991-3, but unusable due to a 10% response rate), CIS2 (1994-6) and CIS3 (1998-2000). The CIS survey covers manufacturing and services but not retailing and government. CIS3 sampled 19,625 firms with an overall response rate of 42%. CIS2 has a similar response rate but sampled only about one quarter as many firms. The CIS2 and CIS3 balanced panel contains 787 firms.

A number of issues immediately arise with respect to survey methods. First, though voluntary, the CIS is an official government survey done and has a high response rate relative to many unofficial surveys. Second, regarding non-response, ONS sent two follow-up CIS questionnaires after the initial mailing, and then contacted the firms by telephone. We checked non-response using the CIS sampling frames and matching it with Business Register data and found non-respondents to be larger than respondents, on average.[5] In most of our regressions below, we therefore control for employment. Third, the CIS survey is at firm level. It could therefore be that multi-plant firms are exporting in only some plants and not others but their productivity is dominated by, for example, the non-exporting plants. Thus we enter controls for multi-plant status.

The key variables for our purposes will be productivity, exporting and learning. CIS contains information on turnover and employment, in terms of full-time equivalents, but does not contain information on material costs and capital so that we are limited to estimate labour productivity equations rather than TFP growth equations.[6] Before going into the details of each question, and since we shall be using lags and fixed effects, it will be important to understand the timing of the CIS questions and answers. The following diagram shows the arrangement of the CIS.

Arrangement of CIS questionnaires




CIS2 and CIS3 ask for output, employment and exporting information[7] in the start and end years of the survey, respectively 1994 and 1996 and 1998 and 2000. These data are marked as Y, N and EXPORT at each node point. They then ask for learning at any time between the start and end dates in the survey. Learning is denoted by the arrows, between 1994 and 1996 and between 1998 and 2000. Thus, with both cross sections of the data available we can form a panel and thereby investigate lags. Also, since the learning occurs at any time over the span of the survey we cannot be absolutely sure that, for example, exporting in 1998 preceded reported learning between 1998 and 2000. Thus to investigate lagged effects we shall look at, for example, learning between 1994 and 1996 on productivity between 1998 (or sometimes 1996) and 2000.

Regarding learning, the case-study evidence suggests that firms learn about new techniques and methods from the experience of exporting, most notably from their customers.[8] How does this match with CIS questions? The CIS asks firms to ***"Please indicate the sources of knowledge or information used in your technological innovation activities, and their importance during the period***". *(please tick one box in each row)*

| | | N | L | M | H |
|---|---|---|---|---|---|
| ***Internal*** | | | | | |
| | *Within the enterprise* | | | | |
| | *Other enterprises within the enterprise group* | | | | |
| ***Market*** | | | | | |
| | *Suppliers of equipment, materials, components or software* | | | | |
| | *Clients or customers* | | | | |
| | *Competitors* | | | | |
| ***Institutional*** | | | | | |
| | *Universities or other higher education institutes* | | | | |
| | *Government research organisations* | | | | |
| | *Other public sector e.g. business links, Government Offices* | | | | |
| | *Consultants* | | | | |
| | *Commercial laboratories/ R&D enterprises* | | | | |
| | *Private research institutes* | | | | |
| ***Specialised*** | | | | | |
| | *Technical standards* | | | | |
| | *Environmental standards and regulations* | | | | |
| ***Other*** | | | | | |
| | *Professional conferences, meetings* | | | | |
| | *Trade associations* | | | | |
| | *Technical/trade press, computer databases* | | | | |
| | *Fairs, exhibitions* | | | | |
| | *Health and safety standards and regulations* | | | | |

where the column answers to columns are N (not used) and L, M, H, respectively low, medium and high (which we code as 0, 1, 2 and 3, respectively). Following the case study evidence, we focus on the variable "clients and customers".

### *3.2 Specification of learning variable*

The main problem with the learning measures is that they are self-reported and use Likert scales. Both may make inter-respondent comparisons difficult. To clarify this point and how we attempt to solve it, assume we have two types of firms, an "optimist" firm, firm O, and a "pessimist" firm, firm P. Suppose that in reality both learned from their clients to exactly the same extent. Because of its "optimism", firm O, might state that all sources of knowledge are important to her, and therefore score all 2. Firm P, because of its "pessimism", might score all 1. If we compared these two scores directly, we would impose that firm O learned more than firm P, which would be wrong. Further, if optimism were positively correlated with performance, we would find a correlation between reported learning and performance which was merely due to the unobserved firm type O.

To control for the unobserved firm type, here pessimism or optimism, we proceed as follows. First, we rescale each learning source by subtracting off the average score over all learning sources for that particular firm. So, for example, when we look at learning from customers for any firm i, we look at the learning relative to the average of all J learning sources in that firm ($LEARN_i^{CUSTOMERS} - \overline{LEARN_i}$) where $\overline{LEARN_i} = (1/J)\sum_j LEARN_{j,i}$ . Thus in our above example, both the O and P firm score a zero in this transformed variable, which, under these assumptions, gives us the correct inter-firm learning comparison.

We take a second step after this transformation which can be seen as follows. Now consider a slightly different case where for both firms learning from customers is in reality more important than other learning sources, and so O gives this source a 3 and other sources a 2, and P gives 3 and 1 respectively. The transformation from mean approach, under these assumptions, correctly re-scales the variables to enable inter-firm comparisons, but the number so generated, depends on assuming that the underlying low, medium and high are linearly related. Since we do not wish to make this assumption, we transform the deviation from mean variable into an indicator function

$$\begin{aligned} &I(LEARN)_i^j = 1 \ \ if \ \ LEARN_i^j - \overline{LEARN}_i > 0 \\ &I(LEARN)_i^j = 0 \ \ otherwise \end{aligned} \tag{4}$$

which says that a learning source j scores one whenever the particular source has a higher score than the average for the firm and zero otherwise.

A number of points are worth making. First, this procedure assumes that the unobservable firm effect affects the reporting of all sources of learning *in the firm* in the same way. An alternative is to assume that all firms tend to report *a particular learning source* in a particularly exaggerated way e.g. if a learning source is particularly "fashionable" at that time. Thus we shall experiment with constructing indicators based on the deviation from the average response of each learning source across all firms (rather than the above, which is the average response of all learning sources for each firm). Second, we also enter $\overline{LEARN}_i$ as a control. Third, in all specifications we enter industry (and time and region dummies) so that any effect common to industries and regions is controlled for. In some specifications we enter firm dummies as well as an additional control. Fourth, the data do not have prices attached to them so we cannot tell whether such information flows are free and so whether they are the source of possible externalities.

Finally, concerning the other measures, we use a dummy for exporting, defined as a 1 if they export and zero otherwise (this is in case the export value is misreported, but we shall experiment with this). Labour productivity is measured as a continuous variable, as the ratio of turnover to employment.

Table 1 summarises the main variables. In the upper panel we see that about 46% of firms in the sample export, and that average employment is 271 FTEs. US, other foreign and UK MNEs account for 4%, 9% and 10% of the sample, and 42% of the sample are multi-plant.

In the difference results below, the identification of the exporting impacts will be from the transitions of firms between exporting status. Table 2 shows the exporting transition matrix between 1994 – 2000, over the two waves of the CIS. The first row of the Table shows that 35 firms who did not export in 1994 start exporting in 1996; 95 export by 1998 and 111 by 2000. Similarly, column 1 tells us that of the firms that did export in 1994, less than 10 had stopped exporting in 1996; 50 had stopped by 1998 and 42 where not exporting in 2000. The rest of the rows and the columns give us a similar description of the changes between 1996, 1998 and 2000.[9]

# 4 Results

### *4.1 Comparison with other work: reduced form labour productivity and exporting*

We first report a reduced form relation between productivity and exporting by estimating

$$\left.\begin{array}{r}\ln(Y/N)_{it}\\ \Delta\ln(Y/N)_{it}\end{array}\right\} = \beta_1 EXPORT_{it-\tau} + \beta_2 \ln N_{it-2} + \sum_{m=1}^{6}\beta_m D_{it}^{m} + \lambda_i + \lambda_I + \lambda_R + \varepsilon_{it} \qquad (5)$$

where in some specifications the dependent variable is ln(Y/N) and in others Δln(Y/N). On the right hand side, EXPORT is a 1/0 variable denoting whether the firm is an exporter and we experiment with different lag lengths, $\tau$. $D^m$ is vector of *m* structural variables that might affect productivity, denoting whether the firm has recently merged, recently started up, is part of a multi-plant operation, is a US multi-national, a UK multi-national or a non-US foreign owned multi-national. The $\lambda$ variables are firm, two digit industry and region dummies. Note that the use of the level of ln(Y/N) means this regression does not really correspond to the model in (1) so is best understood as a description of the data and as a comparison with previous studies. Note too that we do not have data on K, or other inputs.

Table 3, column 1 reports the coefficient and standard error of $\ln(Y/N)_{it}$ on $EXPORT_{it}$, and shows a 24% export productivity premium, similar to other studies (columns 1 to 3 omit $\lambda_i$). To examine selection, column 2 reports the coefficient on a regression of $EXPORT_{it}$, on $ln(Y/N)_{t-2}$ and shows a positive and significant effect. This is again in line with other studies and shows that firms who later export are 24% more productive in the two years before exporting. To get closer to establishing causation, column 3 shows results of estimating $\ln(Y/N)_{it}$ on $EXPORT_{i,t-2}$, and shows that exporters are 25% more productive two years later.

These results compare closely with other studies. For the UK, Kneller and Greenaway (2005) who use accounting data from OneSource and FAME datasets (11,225 firms, 1989-2002) find exporting premia, controlling for three-digit industry, of 11.4% for labour productivity. Our number of 25% likely reflects the fact that their data sets, as they say, consist mostly of large firms whereas CIS is somewhat biased to smaller firms. If large firms are more likely to be exporters then it could be that their data picks up fewer differences between exporters and non-exporters than between small and large firms. Interestingly, our numbers look closer to the US numbers on all firms of Bernard and Jensen (1999, table 1) who report 17% for 1992.

Columns 4 to 6 in Table 3 report a first differenced version of (5) and so control for $\lambda_i$. Column 4 shows that firms who change their exporting status have increased productivity growth two years later. To better interpret this change, we distinguish, as others have done, the different mechanisms behind the change in exporting status: we distinguish between firms who never export (the reference group) and firms who change their status. This latter group consist of firms starting exporting, stopping exporting and firms who continue exporting (for the latter firms the export dummy is 1 in both periods according to our measure, and therefore they will have a zero in the differenced equation, but to distinguish them from the firms who never export – our reference group - we assign them a dummy).[10] Column 5 looks at this effect and suggests that, in quantitative terms most of the effect comes from firms who start exporting. Column 6 shows a first differenced equation using $EXPORT_{t-6}$ as an instrument for $EXPORT_{t-2}$-$EXPORT_{t-6}$. This effect is statistically significant.

Finally, column 7 reports results with $\Delta\ln(Y/N)$ as the dependent variable. The effect of lagged exports is negative. Note that in our data, there is a negative effect of EXPORT on $\Delta\ln Y$ and no effect on $\Delta\ln N$.[11] In terms of other work, those that look at the correlation between $\Delta\ln(Y/N)$ and EXPORT find mixed results, see Wagner (2006) for a survey. Several papers have found no significant difference in labour productivity growth rates between exporters and non exporters: for example Isgut

(2001) using data for Colombia; Bernard (1995) for Mexico; Liu, Tsou and Hammitt (1999) for Taiwan over the period 1989-1993; and Jensen and Musick (1996) for the US. Other studies find exporters have higher productivity growth (e.g. Baldwin and Gu (2003) for Canada; Van Biesebrock (2003) for Sub-Saharian African countries and Sinani (2003) for Estonia) and still others lower productivity growth (e.g. Bernard and Jensen (2004) for the US and Bernard and Wagner (1997) for Germany).

### *4.2 Learning results*

The following sections try to see if there is any support for the learning-by-exporting hypothesis by exploring first the relation between exporting and direct measures of learning. Our estimating equations for learning from the *j* sources are

$$I(LEARN)^{j}{}_{i,t} = \delta_1^j EXPORT_{it-\tau} + \delta_2^j \overline{LEARN}^{j}{}_{i,t} + \delta_3^j \ln L_{it-1} + \sum_{m=1}^{6} \beta_m^j D_{it}^m + \lambda_i^j + \lambda_I^j + \lambda_R^j + \varepsilon_{it}^j \qquad (6)$$

where the left hand side is the learning indicator variable which refers to learning from the *j*'th source over the period 1998-2000. The following points are worth noting. First, in some of the regressions, we also first difference to remove firm-fixed effects (and use industry and region dummies to capture any other effects). Second, we experiment with the dating of the export term, but the results of perhaps most interest are those when EXPORT is dated in 1996, before the learning period (1998 to 2000) to try to help with endogeneity concerns. When we difference (6) we do not have exporting in 1992 to predate the 1996/1994 period and so are forced to use ($EXPORT_{i,96}$ - $EXPORT_{i,94}$).

Regarding econometric method, in (6) the dependent variable is a (0/1) dummy, suggesting a discrete response model. In fact we used a linear probability model (LPM) estimated by OLS: the marginal effects from a probit on the pooled data were very similar to OLS. A LPM also makes first differencing straightforward.[12]

Table 4 sets out the estimates of (6). Columns 1 to 6 have $I^{CUSTOMERS}$ (or its difference) as their dependent variable, since this variable is what the case-studies suggest is of particular importance. Column 1 starts with *EXPORT* dated contemporaneously. As the column shows, the exporting term is strongly significant. To examine selection, column 2 looks at learning *in the past* against exporting *in the future*, where firms are those who exported in either 1998 or 2000. Interestingly, there is no remotely significant relation. This suggests that it is not the case that firms who export, were, in previous periods, learning more from clients. It is notable that this differs from the common finding that firms are highly productive *before* they export, see above, and suggests that there are less serious reverse causality issues in the relation between exporting and learning. Note also that we cannot run the equation reported in column 2 on the full sample of 1,418 but only for the balanced panel sample of 749. The reason for this is that learning is only available over a three year period, so that we only have two periods for the learning variables 1994 to 1996; and 1998 to 2000; while we have four points in time for exporting, i.e. 1994; 1996; 1998 and 2000. Also the regression sample is restricted to the firms who were not exporting in 1994-1996; i.e. to 403 firms.

Column 3 is the regression of perhaps most interest, namely lagged exports as a determinant of current learning. There is a significant relation, suggesting that previous exporting is associated with current learning from clients. This uses the same sample as in column 2 to check that the significance of past exporting status on reported learning from buyers does not disappear when we restrict the sample to be the same as the one in column 2, i.e. 403 observations. The coefficient is significant at the 5% level but less precisely estimated than in column 4 where we use the same sample as column 1.

Column 5 is a first differenced version of column 4 and shows the relationship weakening in significance but the coefficient being very similar to that found in column 4. To explore the differences in the exports effect more, column 6 shows the coefficients associated with starters, stoppers and continuers, as in Table 2. Once again, most of the quantitative effect comes from starters, in line with the results from the reduced form presented in Table 3 (the relevant p values are 16.3%, 43.9% and 33.4%). Note that since in columns 5 and 6 the dependent variable is changes in learning from customers between 1994 and 1996 and between 1998 and 2000 regressed on the change in Exporting dated 1994 and 1998, the sample is limited to the 749 firms in the CIS2-CIS3 panel for which we can construct this variables.

Columns 7 to 9 check whether our findings regarding $I^{CUSTOMERS}$ are spurious by using other learning types, $I^{SUPPLIERS}$, $I^{COMPETITORS}$ and $I^{TRADEASSOC}$ regressed on $EXPORT_{t-2}$. As the table shows the correlations in levels (columns 7 to 9) are all statistically insignificant at conventional levels. The same is the case for differences and also for other information sources.[13]

In summary, the table has looked at $I^{CUSTOMERS}$. Our levels results show that firms who export report, two years later, statistically significantly more learning from buyers (i.e. $I^{CUSTOMERS}$, learning relative to other learning sources). Our difference results are less statistically significant but they suggest that firms who change their exporting status, report, two years later, increased $I^{CUSTOMERS}$ (with 87% confidence) but no remotely statistically significant effect on any other forms of learning. We now move on to see how such learning affects productivity growth.

### *4.3 Productivity growth results*

To examine the relation between productivity and learning we estimate

$$\ln(Y/N)_{i,t} - \ln(Y/N)_{i,t-4} =$$
$$\beta_1^j I(LEARN)^j{}_{i,(t-6/t-4)} + \beta_2^j \overline{LEARN}^j{}_{i,(t-6/t-4)} + \beta_3^j \ln N_{i,t-4} + \sum_{m=1}^{6} \beta_m D_{it}^m + \lambda_i + \lambda_I + \lambda_R + \varepsilon_{it} \quad (7)$$

where the left-hand side variable is productivity growth between 1996 and 2000 and $I(LEARN)_{(t-6/t-4)}$ stands for leaning between 1994 and 1996 and again note that we have used differences to try to remove firms' fixed effects, and lags to try to control for selection and D also contains learning from within the firm, to proxy for R&D and such like that might affect productivity growth.

One important point is that we do not have data on K (and other physical inputs) and so these are omitted variables in (7). To the extent that $I^j$ is correlated with these variables, and they are not measured by the included regressors, we are not of course estimating the effect of I on TFP growth, but on labour productivity growth.

The results of estimating (7) are set out in Table 5, where we start by including just I(*LEARN*)$^{CUSTOMER}$. Column 1 shows the estimate of (7), omitting, for the moment, $\overline{LEARN}$, measured independently. The effect of I(*LEARN*)$^{CUSTOMER}$ is statistically significant. Column 2 adds $EXPORT_i$ dated 1994. The effect is negative, with the coefficient on I(*LEARN*)$^{CUSTOMER}$ falling somewhat. Column 3 includes $\overline{LEARN}$ and whilst the precision of I(*LEARN*)$^{CUSTOMER}$ falls, it is still significant at the 10% level. Column 4 enters $I(LEARN)^{CUSTOMER}$ and $\overline{LEARN}$ and $EXPORT_i$; the coefficient on learning is still significant at the 10% level.[14]

Finally, to test if the oppositely timed relationship is true, we regressed learning from clients on past productivity growth and found no significant effect (results available upon request).

To summarise, these results suggest that firms who report more learning from customers, relative to other forms of learning, are statistically significantly more likely to experience increases in labour productivity 2 years later. But the reverse relation does not hold, namely that firms who have increased labour productivity are not statistically significantly more likely to have more learning from customers two years later.

## 5 Conclusion and discussion

The learning-by-exporting hypothesis postulates that firms learn in ways that enhance their performance via exporting. Most papers examine this hypothesis indirectly by looking at exporting (possibly lagged) and productivity growth. To examine it directly, we assemble a new UK panel data set with firm-level information not only on productivity and exporting but also on the mechanisms through which firms learn in order to innovate. We can therefore examine whether there is any systematic evidence that exporting firms have different learning intensities relative to non-exporting firms. We use the panel element in the data to control for fixed effects and explore timing but of course, since our data are not experimental, inferring causation is problematic. But, to the best of our knowledge, there are almost no *direct* tests of the learning-by-exporting hypothesis and so we think that such direct evidence, even if only of correlations, is of interest.

Regarding exporting and productivity, our data yields similar correlations between productivity and exporting to other data sets: e.g. a productivity advantage of about 24% for exporters; more productive firms in advance of exporting then export; etc. This makes a small addition to the UK evidence base and suggests that our data, at least in these dimensions are reliable.

Regarding the learning-by-exporting hypothesis, which suggests that firms improve by learning from exporting, we have data on the extent to which they learnt from buyers, suppliers, other firms etc. in innovating. We have a number of, we believe, interesting findings. First, in both levels and in differences, past exporting is associated with statistically significantly more learning from buyers (relative to other sources), in line with the learning-by-exporting hypothesis (and in differences the effect is significant at the 13% level). Second, in both levels and differences, past exporting is *not* associated with statistically significantly more learning from other sources. This suggests that if the causation from past changes in exporting to changes in learning is caused by unobservables, they would have to be changes in unobserved factors that affected changes in exporting and changes in learning from clients but not changes in learning from other sources.

Our third finding is that the reverse timing is not the case: past learning is not statistically significantly associated with more exporting, indicating no evidence for pre-exporting sorting by learning and non-learning firms. Fourth, past learning from buyers (relative to other learning) is associated with statistically significantly higher productivity growth while again, the converse - that past productivity growth is associated with more learning - is not the case. Finally, past learning from other sources is not associated with more productivity.

In sum, our results suggest some support for the learning-by-exporting hypothesis from these direct learning measures and that tests of this hypothesis might have been obscured in other work by the noise in indirect measures like TFP and labour productivity growth.

We have three final points. First, whilst our results are suggestive of the learning-by-exporting effects they do not of course rule out pre-exporting sorting (and indeed our pre-exporting productivity correlations support this). Thus empirically it could of course be that the overall productivity growth/exporting relation is dominated by sorting. Second, we emphasise that we cannot measure TFP and so our results here are only for labour productivity.

Third, do our results support subsidies to exporters? Not necessarily. Assuming such intervention is justified on the basis of externalities, it would have to be the case that exporting firms, who learn from the experience, convey non-internalised externalities to other firms in the UK. Whether or not exporting affects labour productivity growth, as we have shown here, further investigation would have to establish if exporting of one firm might affect productivity in others. However, it is interesting to note that our findings suggest that learning effects are mostly confined in new exporters. If such learning spills over then this suggests that subsidies should be directed at new exporters and not to all exporters.

Table 1: Summary statistics

Descriptive Statistics-Pooled Sample (1994,1996,1998,2000)

| Variable | Obs | Mean | Std. Dev. |
|---|---|---|---|
| X (0/1) | 3120 | 0.46 | 0.50 |
| Turnover (£000) | 3120 | 52533.89 | 537257.70 |
| Employ | 3120 | 271.31 | 824.45 |
| (Y/N) (£000) | 2962 | 112.17 | 240.58 |
| US MNE | 3120 | 0.04 | 0.19 |
| Non US MNE | 3120 | 0.09 | 0.29 |
| UK MNE | 3120 | 0.10 | 0.29 |
| Multiplant | 3120 | 0.42 | 0.49 |

**Note:** CIS2 and CIS3. Other learning variables not shown for brevity. Employ is employment in FTE. Y/N is productivity defined as turnover over employ. US MNE is a 1/0 indicator variable valued 1 if the firm is part of a US multi-national enterprise (MNE), Non-US and UK are similar according to being part of a non-US and UK MNE respectively. Multiplant is valued at 1 is the establishment is part of a multi-plant firm.

Table 2: Transition Matrix for exporters between 1994 and 2000

| | YES | | | |
|---|---|---|---|---|
| NO | 1994 | 1996 | 1998 | 2000 |
| 1994 | | 35 | 95 | 111 |
| 1996 | <10 | | 75 | 89 |
| 1998 | 50 | 62 | | 31 |
| 2000 | 42 | 52 | <10 | |

**Note:** On average in each period 671 firms do not change exporting status relative to the previous year. <10 means there are less than 10 observations in the cell. 10 observations is the threshold for disclosure set by the UK Office for National Statistics.

Table 3: Labour productivity and exporting

(estimates of (5), dependent variable ln(Y/N) or ΔlnY/N as indicated)

| | Column 1 | Column 2 | Column 3 | Column 4 | Column 5 | Column 6 | Column 7 |
|---|---|---|---|---|---|---|---|
| Regressor dating | Contemp | Before | After | After | After | After | Growth After |
| Levels, method | Levels | Levels | Levels | FD | FD,status | FD,IV | Levels |
| Dependent | lnY/N(i,t) | lnY/N (i,t-2) | lnY/N (i,t) | [lnY/N (i,t)- lnY/N (i,t-4)] | [lnY/N (i,t)- lnY/N (i,t-4)] | [lnY/N (i,t)- lnY/N (i,t-4)] | [lnY/N(I,t)- lnY/N (i,t-4)] |
| X(i,t) | 0.2357 | 0.2415 | | | | | |
| | [0.0498]*** | [0.0592]*** | | | | | |
| X(i,t-2) | | | 0.2473 | | | | |
| | | | [0.0479]*** | | | | |
| [X(i,t-2)-X(i,t-6)] | | | | 0.1177 | | 0.225 | |
| | | | | [0.0705]* | | [0.1112]** | |
| X(i,t-2)>0,X(i,t-6)=0 | | | | | 0.1586 | | |
| | | | | | [0.1035] | | |
| X(i,t-2)=0,X(i,t-6)>0 | | | | | -0.0037 | | |
| | | | | | [0.0858] | | |
| X(i,t-2)>0,X(i,t-6)>0 | | | | | -0.0718 | | |
| | | | | | [0.0623] | | |
| X(i,t-6) | | | | | | | -0.1154 |
| | | | | | | | [0.0571]** |
| Observations | 2147 | 1027 | 1408 | 738 | 656 | 738 | 738 |
| R-squared | 0.3 | 0.3 | 0.32 | 0.09 | 0.1 | 0.08 | 0.09 |

**Note:** X stands for EXPORT, a 1/0 dummy according to whether exporting is positive or not. The sample is a pool of CIS2 and CIS3. Control variables included are 2 digit sector dummies, regional dummies, structural changes (start-up and mergers), multiplant and ownership dummies. We also control for lag (log) size. Labour productivity is computed as turnover over employment (full time equivalents) and the growth rate is over a two years period. Robust standard errors clustered for within firm correlation in parenthesis. Samples are as follows. Column 1, all cross sections, 2000, 98, 96 and 94. In column 2 the sample is restricted to all firms that did not export in 1994 (t-6) and 1996 (t-4). Some of them did start exporting in 1998 (t-2) or 2000 (t). Column 3 includes cross-sections 2000, 98 and 96. In columns 4, 5 and 6, the dependent variable is Δ(96 to 2000) and the regressors Δ(94 to 98). In column 7 the dependent variable is Δ(96 to 2000) and the regressors 94. Estimation by OLS except for column 6 which is by IV: the instrument used in column 6 is EXPORT dated 94 for ($X_{98} - X_{94}$).

Table 4: Exporting and learning (all learning variables are in deviation from the average learning of the firm)

(estimates of (6), dependent variable I(LEARN))

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Learning | Contemp Levels | Before Levels | After Levels | After Levels | After FD | After FD,Status | After Levels | After Levels | After Levels |
| | I(Learn(i,t)) | I(Learn(i,t-4) \| Learn(i,t-6)) | I(Learn(i,t)) | I(Learn(i,t)) | I(Learn(i,t)-Learn(i,t-4)) | I(Learn(i,t)-Learn(i,t-4)) | I(Learn(i,t)) | I(Learn(i,t)) | I(Learn(i,t)) |
| From | Clients | Clients | Clients | Clients | Clients | Clients | Suppliers | Competitors | Trade Assoc |
| X(it) | 0.1171 | | | | | | | | |
| | [0.0332]*** | | | | | | | | |
| [X(i,t)>0 \| X(i,t-2)>0] | | -0.0226 | | | | | | | |
| | | [0.0703] | | | | | | | |
| X(i,t-2) | | | 0.171 | 0.0888 | | | 0.0545 | 0.0191 | 0.047 |
| | | | [0.0835]** | [0.0334]*** | | | [0.0359] | [0.0352] | [0.0300] |
| [X(i,t-2)-X(i,t-6)] | | | | | 0.0981 | | | | |
| | | | | | [0.0650] | | | | |
| X(I,t-2)>0,X(i,t-6)=0 | | | | | | 0.1308 | | | |
| | | | | | | [0.0936] | | | |
| X(I,t-2)=0,X(i,t-6)>0 | | | | | | -0.0961 | | | |
| | | | | | | [0.1242] | | | |
| X(I,t-2)>0,X(i,t-6)>0 | | | | | | 0.0726 | | | |
| | | | | | | [0.0751] | | | |
| Observations | 1418 | 403 | 403 | 1418 | 749 | 749 | 1418 | 1418 | 1418 |

**Note:** X stands for EXPORT, a 1/0 dummy according to whether exporting is positive or not. The sample is a pool of CIS2 and CIS3. Control variables included are 2 digit sector dummies, regional dummies, structural changes (start-up and mergers), multiplant and ownership dummies. We also control for lag log(size). In all the regressions the dependent variable is learning "relative" to the average of the remaining sources. Samples are as follows. Column 1, the dependent is learning between 98 and 00 and between 94 and 96, X is dated 96 and 2000. Column 2 and 3 are for firms who do not export in 94 and 96 but do in 98 or 2000, whilst learning is learning between 94 and 96. Column 4 is learning between 94 and 96 and between 98 and 2000, with X dated 94 and 98. In columns 5 and 6 the dependent variable is the change in learning between 94 and 96 and between 98 and 2000 on the change in X dated 94 and 98. Columns 7, 8 and 9 are as column 4. Robust standard errors in parentheses.

Table 5: Learning and labour productivity growth

(estimates of (7), dependent variable [ln(Y/N)(i,t)- ln(Y/N) (i,t-4)])

| | Column 1 | Column 2 | Column 3 | Column 4 |
|---|---|---|---|---|
| | OLS | | OLS | |
| $I(LEARN)^{CUSTOM}$ (i,t-4) | 0.0919 | 0.0877 | 0.0701 | 0.0635 |
| | [0.0368]** | [0.0367]** | [0.0382]* | [0.0382]* |
| $\overline{\text{LEARN}}$ (i,t-4) | | | 0.0575 | 0.0591 |
| | | | [0.0301]* | [0.0301]* |
| Export(i,t-6) | | -0.0716 | | -0.0729 |
| | | [0.0275]*** | | [0.0273]*** |
| Observations | 755 | 755 | 755 | 755 |
| R-squared | 0.07 | 0.08 | 0.08 | 0.09 |

**Note:** The sample is a pool of CIS2 and CIS3. Control variables included are 2 digit sector dummies, regional dummies, structural changes (start-up and mergers), multiplant and ownership dummies. We also control for lag (log) size. Robust standard errors in parentheses. The left hand side is log labour productivity growth between 1996 and 2000, the right hand side is learning between 1994 and 1996. Exports are dated 1994.

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lead footnote*Contact: Jonathan Haskel, Queen Mary, University of London, Economics Dept, London E1 4NS, j.e. haskel@qmul.ac.uk. Phone Number +44 (0) 20 7882 5365 Financial support for this research comes from the ESRC/EPSRC Advanced Institute of Management Research, grant number RES-331-25-0030. Chiara Criscuolo acknowledges the ESRC, grant number PTA-026-27-0445, and the British Academy for funding. This work was carried out at The Centre for Research into Business Activity, CeRiBA, at the Business Data Linking Branch at the ONS and contains statistical data from ONS which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates. We thank the BDL team at ONS as usual for all their help with computing and facilitating research. We thank two anonymous referees and the editor for extremely valuable comments. All errors are of course our own.

[1] The motivation for the relation between exporting and learning is mostly based on case study evidence, for formal theory, see below. For case-studies and anecdotal evidence, see for example Kraay (1999); Blalock and Gertler, (2004) and quotes in Clerides et al. (1998). For econometric evidence see Bernard and Jensen (1997; 1999 and 2004) and De Loecker, (2004) and Kostevc, (2005), on Slovenia; Greenaway and Kneller, (2004) on the UK. The list of existing work on exporting and productivity is much richer: Van Biesebroeck, (2005), on Africa; Delgado et al, (2002) on Spain; Castellani, (2002) on Italy; Aw, Chung et al, (2000) on China and Korea to cite a few. For a more complete list of the studies with details on methodologies and results see the review by Wagner, (2006). Javorcik (2004) using data from Lithuania finds that the productivity growth of domestic firms is positively correlated with the presence of foreign owned firms in downstream sectors, consistent with learning of upstream firms from their (foreign) customers.

[2] Our productivity/exporting correlations confirms findings by the existing (small) UK literature and are in line with evidence from other countries, see the review by Wagner (2006).

[3] Recent work by Salomon and Shaver (2006) uses innovation and patent application counts as a more direct outcome of learning from exporters relative to productivity. Using Spanish data they find that exporters increase their patent applications and their product innovations subsequent to exporting which is consistent with the learning-by-exporting hypothesis.

[4] Finally, note that many studies estimate a relationship between *levels* of EXPORT and the *level* of labour productivity, i.e. (1) with ln(Y/N) on the left-hand side which we shall also do to check how our data relates to others.

[5] A detailed analysis of characteristics of non-respondents in terms of employment and industry distribution can be found in Criscuolo et al. (2003).

[6] This means that positive correlations between exporting and productivity and learning and productivity might be driven by increased capital and material costs to labour ratios beyond the increase in A.

[7] Output is asked for as "Total turnover (market sales of goods and services including export and taxes except VAT in current prices)", employment as full time equivalents and exporting as "value of exports of goods and services".

[8] Consider the following quotes set out in Clerides, Lach and Tybout (1998). "*…a good deal of the information needed to augment basic capabilities has come from the buyers of exports who freely provided product designs and offered technical assistance to improve process technology in the context of their sourcing activities. Some part of the efficiency of export-led development must therefore be attributed to externalities derived from exporting* {Evenson and Westphal 1995}, or "*The important thing about foreign buyers, many of which have offices in Seoul, is that they do much more than buy and specify. . . . They come in, too, with models and patterns for Korean engineers to follow, and they even go out to the production line to teach workers how to do things*" {Rhee, Ross-Larson, and Pursell 1984, p. 41}.

[9] We cannot report marginal figures for confidentiality reasons.

[10] So $\Delta EXPORT = EXPORT_t - EXPORT_{t-1}$ is classified in four categories:

$$Reference\ group:\quad X_t = 0, X_{t-1} = 0 \qquad never\ exporting$$

$$X_t - X_{t-1} = \begin{cases} X_t > 0, X_{t-1} = 0 & starters \\ X_t = 0, X_{t-1} > 0 & stoppers \\ X_t > 0, X_{t-1} > 0 & continuers \end{cases}$$

11 We explored further versions of this all of which gave a similar answer. As well as the dummy variable that indicates whether a firm exports, we added a second variable that interacts the demeaned log export intensity with this dummy variable. This dummy then captures the effect of exporting for the exporting firm of average export intensity relative to the non-exporter; while the coefficient on the interaction variable measures the effect of a 1% increase in export intensity relative to the average export intensity.

[12] The case for the linear probability model is strengthened in that that almost all our regressors are discrete (see Wooldridge, 2002, p.456). A problem with a conditional logit model is that the only identifying power comes from firms who change information status. This is a small number in our sample.

[13] We only show the results for three cases learning from suppliers and competitors, as these have been suggested as possible learning sources for exporters; the results for the remaining ones were similar. Other robustness checks were to look at the relation between $I^{CUSTOMER}$ and EXPORT at the start of the period for the 1998-2000 and 1994-96 separately, both of which returned significant effects. We also recalculated $I^{CUSTOMER}$ as the deviation from the mean answers to the customer learning question for all

firms and as the deviation from the mean answers to all learning sources in all firms. Both returned significant coefficients when regressed on $EXPORT_{t-2}$. Finally, we also obtained significant effects from EXPORT when measuring export intensity, defined as export amount divided by turnover. These results are available upon request.

[14] We also obtained a significant effect of $I^{CUSTOMER}$ on productivity growth with the two other ways of generating the deviation of learning from the mean, see note 13.