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

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Abstract

Case study evidence suggests that exporting firms learn from their clients. But econometric evidence, mostly using exporting and TFP growth, is mixed. We use a UK panel data set with firm-level information on exporting and productivity. Our innovation is that we also have direct data on the sources of learning (in this case about new technologies). Controlling for fixed effects we have two main findings. First, we find firms who exported in the past are more likely to then report that they learnt from buyers (relative to learning from other sources). Second, firms who had learned from buyers (more than they learnt from other sources) in the past are more likely to then have productivity growth. This suggests some support for the learning-by-exporting hypothesis, though is not clear whether firms deserve an exporting subsidy.

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1 Introduction

There is an extensive theoretical and empirical literature on productivity and exporting at the firm level. Given the prevalence of export-supporting policy and the importance of productivity in determining living standards, this is an important area for policy and welfare. There are at least three important topics in the empirical literature. First, what are the correlations between productivity and exporting? Second, can one establish causation from exporting to productivity or *vice versa*? Third, one theoretical explanation of why exporting might cause productivity improvements is *the learning-by-exporting hypothesis*, i.e. firms learn as a consequence of exporting: is this supported in the data? [1]

This paper attempts to contribute to these three questions using a UK firm-level dataset that has not, to the best of our knowledge, been used before.[2] First, on correlations, we use information on exporting and labour productivity to examine productivity/exporting correlations. There is already a (small) UK literature on this question and so whilst our results are not novel they confirm these results using a different data set.

Second, on causation, we have data on exporting and productivity at four points in time. Thus we can use the time series in the data to examine whether firms that have initially high productivity *later* export or whether exporting firms *later* have higher productivity etc. Whilst this cannot establish causation in the way that experimental data would be able to, it is at least likely more helpful than simple cross-section calculations. Once again, we contribute to the small UK literature on these dynamics.

Finally, on learning, we believe the paper makes a novel contribution. The theory of exporting and learning postulates that firms gain information when exporting and that such learning enhances their productivity. Consider the following quotes set out in Clerides, Lach and Tybout (1998):

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[1] The importance of the productivity/exporting link is set out in e.g. the survey of Bernard and Jensen (2004). As they point out, there appear to be macro links between growth and trade see e.g. Sachs and Warner (1995) and this is a very important policy issue. The micro links underling these macro correlations are not well understood. In theory models e.g. of Bernard et al (2004) and Melitz (2003) ex ante more productive firms export and lowering of trade barriers raises aggregate productivity by shifting market share to such firms and away from less efficient firms. Thus the micro mechanism behind an increase in productivity is a sorting effect rather than a within firm efficiency gain effect. In other models firms learn by exporting.

[2] The only exception that we are aware of is Hanley (2004) who uses one wave of the panel that we use to look at the relation between exporting and size and whether firms use information networks with other firms. She does not , as we do, investigate productivity or learning from buyers.

> *. . . 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}.*

> *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}.*

> *When local goods are exported the foreign purchasing agents may suggest ways to improve the manufacturing process {Grossman and Helpman 1991, p. 166}*

A number of papers have attempted to test these possible avenues by looking at productivity and productivity growth of exporting and non-exporting firms before and after exporting. Perhaps not surprisingly the results differ across methods, but also periods and countries (which might reflect different causal mechanisms over countries and time). We do not wish to adjudicate on the relative merits of these studies, but to simply point out here that whilst many of the above quotes refer to learning via information flows, due to data limitations, the above cited studies are usually about the relationship between exporting activity and productivity (or productivity growth). It would however be of interest to study the information flows *directly*, since total factor productivity growth can be driven by all sorts of other factors besides just increased information flows. The problem of course is that it is very hard to get data on information flows. Our data set contains just these data and so this is the main contribution of this paper.

Our data on productivity, exporting and learning are for a panel of UK firms covering their operations for 1994, 1996, 1998 and 2000 spanning therefore over six years. These data come from two waves of the UK Community Innovations Survey (CIS), an EU-led survey on innovation outputs, inputs and learning. For each firm we have information on productivity and exporting. 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, from within the firm, consultants, competitors etc.). The answers to this question might then potentially shed light on the learning from buyers hypothesis set out in the quotes above. *Thus our test of the learning-by-exporting hypothesis is to examine whether firms who export are later more likely to report learning from buyers (relative to the other types of learning they specify). We then examine whether such learning is related to later productivity growth.* We use the panel structure of the data to see how the correlations vary over time and to control for firm fixed effects. Of course, we are unable to obtain causal estimates on these non-experimental data. But we do find some what we think are interesting correlations on these data, correlations that seem to be robust to e.g. fixed effect controls and the like.

We have two main areas of findings: one concerning the exporting/productivity relation and the other the learning-by-exporting hypothesis. First, concerning the exporting/learning relation, we find what many others also find. As far as contemporaneous correlations are concerned, exporters have 24% more labour productivity. As far as performance before exporting is concerned, exporting firms are more productive before they export. Of all firms who do not export in period *t-k*, firms who then export in period *t* are also 24% more productive than those not exporting in *t*. This supports the idea, found in much of the literature, that there is pre-exporting selection such that better firms then go on to export. And, as far as performance after exporting is concerned, firms raise their performance in the period after exporting.

Our second set of findings concern learning-by-exporting. Regarding levels, we find that firms who had exported two years previously report more learning from clients (relative to other sources of learning). The same holds in differences. Interestingly however, we also find that firms who had changed their exporting status 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. 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. Finally, we find that firms who have had an increase in learning from clients have subsequent productivity growth.

Thus we think the paper has potentially interesting implications for research into learning patterns. Our direct data on learning suggest some support for the learning-by-exporting hypothesis. Now, it might be that we have picked up these correlations that are unique to the UK and the particular period, but it might well be that the reason that others have not found learning effects is they could not look for them directly and their impact has been hidden by the noise in productivity measures.

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

2 Theory

2.1 General approach

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. In what follows, an unsubscripted variable refers to a firm and we have omitted a time indicator. Firms have an output production function, in levels and differences of the form

$$\begin{aligned} &Y = A \bullet F(Z,m) \\ &TFPG = \Delta Y - \Delta F(Z,m) = \Delta A \end{aligned} \tag{1}$$

where Y is real output, A the knowledge stock at the firm, Z are paid for inputs and we assume that m, managerial quality, affects both TFP levels (TFP) and TFP growth (TFPG).

Changes in the knowledge stock, ΔA, arise in the case study evidence from learning (which in turn is affected by exporting). This is captured formally for example in the knowledge production function, Griliches (1979). However, if firms learn about, for example a new machine, which they then buy, it is perfectly possible that learning affects ΔZ as well. Thus we may write

$$\left.\begin{aligned} \Delta Z \\ \Delta A \end{aligned}\right\} = \left\{\begin{aligned} &g(L^{BUYERS}, L^*, m) \\ &h(L^{BUYERS}, L^*, m) \end{aligned}\right. \tag{2}$$

where managerial quality m might affect both factors, L^{BUYERS} is a variable denoting learning from buyers, where we use buyers since that is the terminology used in the case studies quoted in the introduction, L* a vector of learning variables denoting learning from all other sources (e.g. within the firm, universities, competitors etc.) and we are ignoring for the moment any other factors like factor prices or R&D that might affect ΔZ and ΔA.

Finally, learning L from the various sources is likely determined by a number of factors, but here we focus on exporting, X and managerial ability, m. The case studies cited above suggest that exporting provides an avenue by which firms can learn from their buyers. Equally, managerial ability might make firms more able to learn from all avenues *ceteris paribus*. Thus we may write

$$L^{BUYERS} \atop L^* \Bigg\} = \begin{cases} L^{BUYERS}(X,m) \\ L^*(m) \end{cases} \qquad (3)$$

Finally, exporting X itself may be a consequence of learning or indeed other factors, such as exchange rates, managerial ability etc. Thus we can write

$$X = X(L^{BUYERS}, L^*, m) \qquad (4)$$

Let us take the qualitative evidence that firms appear to learn from the exporting experience as true. How would we expect this to show up in quantitative measures? The most straightforward "baseline" case is where, from (3), X affects L, and from (2), L affects ΔA, and from (1), ΔA leads to higher TFPG. However there are a number of different possibilities too.

First, there is the case much discussed in the literature, namely the polar opposite of the baseline where the relationship is all due to selection. Thus let us suppose that a higher *m* drives the relation between X and L in both (3) and (4). Thus from (2) one would observe a positive correlation between L and ΔA and ΔX and so an apparently positive relation between X and TFPG from (1).

Second, is a case that we do not believe has been pointed out, namely where the qualitative evidence of learning is correct, but that this learning is capitalised. Thus from (3), X *does* indeed affect L, but in (2) L affects ΔZ, and hence from (1) there is *no* effect on TFPG. Thus it is perfectly possible for X to casually affect L, but not affect TFPG.[3]

To move forward, the literature has tried to confront a number of issues. The first is to unravel the possible simultaneity between X and L in (3) and (4). Since datasets typically lack information on L, this is done by examining a relation between lagged exports, X_{t-k} and current output, Y_t which implicitly solves the simultaneity problem using lags and the problem of not having L by substituting (2) into (1).[4] The second is to look for non-capitalised effects on TFP

[3] Regarding levels and growth, note that the effect here is from the *level* of exports on the *level* of learning and so on productivity *growth*. This accords with the studies of exporting on later productivity growth in, for example, Bernard and Jensen (1999).

[4] Similarly, many papers find a significant effect of lagged Y/L on future X suggesting that selection is potentially important.

or TFPG. The third is to look for effects on TFPG rather than TFP to try to control for *m* to the extent that m might affect the level of productivity and other variables.

2.2 Our approach

What then do we do? We have panel data on learning, exporting and labour productivity. As it is standard in the literature, we start by looking at the reduced form capturing the relationship between exporting and productivity. Due to data availability, our dependent variable here will be labour productivity and hence, it will not be possible to untangle the impacts of learning through both un-paid (ΔA) and paid inputs (Z), rather we will capture their combined effect on labour productivity. So we start by estimating:

$$\ln(Y/L)_{i,t} = \alpha_1 X_{i,t-2} \qquad (5)$$

(where we omit additional terms such as errors, dummies etc, see below) where we deal with the issue of simultaneity between exporting and productivity by using two year lags and deal with fixed effects problems by estimating a first differenced version of (5). Additionally, any remaining correlation between exporting and the (lag) shocks is controlled for by using instrumental variables.

The next step is to look at the transmission mechanisms underlying (5). Unlike most datasets, we do have direct data on learning, so we believe this is an innovation. On the other hand, we have no "natural experiment" in the data, so we proceed as follows. We start by looking at the relation between L and X in (3) and (4). There are two issues here, simultaneity and unobservables. To look at simultaneity, in the absence of a natural experiment, we proceed as standard and use lags to estimate the effect of X_{t-1} on L using equation (3). Moving to unobservables we take two steps. First, under the assumption that exporting affects learning from the clients but not learning from other sources, we can subtract the two rows of equation (3) to get:

$$(L^{BUYERS} - L^{*})_{i,t} = \beta_1 X_{i,t-1} \qquad (6)$$

i.e. we look *not* at the effect of exports on learning from buyers, but at the effect on learning form buyers *relative* to learning from all the other sources. This should help control for unobservables that affect all dimensions of learning and exporting.

However, this demeaning procedure does not control for unobservables affecting L^{BUYERS} and L* differently.[5] To control also for this issue we use our panel data to estimate a first difference version of (6). As a further check, we replace L^{BUYERS} in (6) with other learning sources (e.g. competitors, suppliers, trade associations etc.) to check that changes in exports do not influence the deviation of learning from its average for other learning types. Thus we also estimate

$$(L^{COMPET} - L^*)_{i,t} = \beta_{11} X_{i,t-1} \qquad (7)$$

Finally, we examine the relation between learning and changes in productivity implicit in (1) and (2) by estimating

$$\ln(Y/L)_{i,t} - \ln(Y/L)_{i,t-1} = \gamma_1 (L^{BUYERS} - L^*)_{i,t-2} + \gamma_2 L^*_{i,t-2} \qquad (8)$$

where productivity growth is a function of the deviation of learning from clients over other sources of learning and we control for the average score of the other sources of learning (they are also explanatory variables in the knowledge production function (2)) . We again use lags to try to control for simultaneity.

Our core findings in this paper revolve around estimates of (6) and (8). In (6) we find that *X* is positive and significant. We do not find it so in (7), suggesting that learning from clients is affected by past exporting while learning from other sources is not. We then find L^{BUYERS}-L^* is significant in (8). All this supports the learning-by-exporting hypothesis.

[5] This is of course quite possible; for example, managers might have language skills that make them able to learn from the exporting experience but not from other learning sources.

3 Data

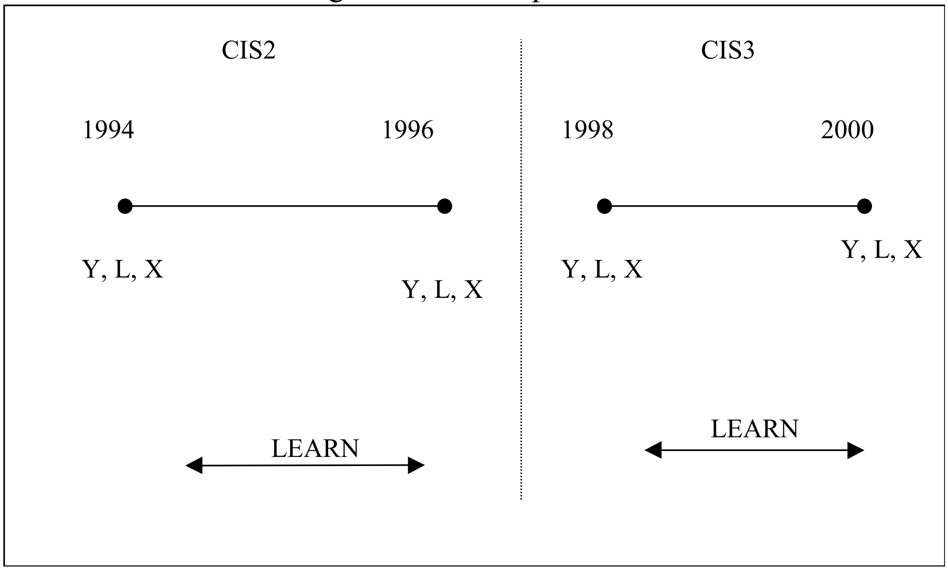
3.1 Data set

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). CIS4 has just finished fieldwork. The CIS survey covers production 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 panel contain 787 firms in common.

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. In most of our regressions below, we therefore control for size (with 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, exports and learning. 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 question and answers. The following diagram shows the arrangement of the CIS.

Arrangement of CIS questionaires



CIS2 and CIS3 ask for output, employment and exporting information[6] in the start and end years of the survey, respectively 1994 and 1996 and 1998 and 2000. These data are marked as Y, L and X at each node point. They then ask for learning at any time between the start and end dates in the survey. Thus learning is denoted by the arrows, between1994-96 and between 1998-2000. 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 time span of the survey we cannot be absolutely sure that, for example, exporting in 1998 preceded reported learning between 1998 and 200. Thus to investigate lagged effects we shall look at, for example, learning between 1994 and 1996 on productivity between 1998 and 2000.

Regarding learning, CIS provides an interesting opportunity to have this information. The quotes set out above suggest that firms learn about new techniques and methods from the experience of exporting, most notably from their buyers. 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 1998-2000. *(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. We focus on the variable "clients and customers" which we call "buyers" for short and we form the regressor of interest by ranking the answers 0, 1, 2 and 3 and taking the deviation of the learning variables from the average of the other variables. We then turn this into a 1/0 dummy for whether the deviation is positive or otherwise.

A number of points are worth making regarding this. First, in principle it would be desirable to have more "objective" measures of learning such as number of emails, phone calls, visits etc. all weighted by their importance in the learning process. These data are very hard to collect and so in their absence we shall use the data we have. Second, 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

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[6] 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".

source of possible externalities. Third, one might worry about the use of Likert scales, which make inter-respondent comparisons difficult. To get over this, we have specified L^{BUYERS} in terms of its deviation from other learning types and we shall also use a panel. Fourth, one might worry that respondents do not respond with accuracy to voluntary questions. To the extent that this adds noise to the data then it biases us against finding statistically significant effects. In addition, to reduce these measurement problems we use dummies for learning and exporting. For exporting, firms have a dummy of 1 if they export and zero otherwise (rather than relying on the possible misreported export value). For learning, firms have a dummy of 1 if the learning from clients exceeds the average of learning from others and zero otherwise. Labour productivity is measured as a continuous variable, as the ratio of turnover to employment.

Table 1 summarises the descriptive statistics for the main variables used in the analysis. 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 lower panel the learning variables have been recoded to a 0/1 dummy (1 for 1, 2, 3 of the Likert scale). The table shows learning from internal sources and clients, which are the key controls that we shall use. The other learning variables are quite collinear. 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 row and the columns give us a similar descriptions of the changes between 1996, 1998 and 2000.

4 Results

4.1 Labour productivity and exporting, reduced form

To compare our work with others we estimate (5) which is, in full,

$$\ln(Y/L)_{i,00} = \alpha_1 X_{i,96} + \sum_{j=2}^{k} \alpha_j D_{jit} + \lambda_I + \lambda_i + \varepsilon_{it} \tag{9}$$

where D_j are the following variables: a constant, size (to control for reporting bias), a vector of status dummies (start-up and merging status, to control for firms newly in production or reorganised), ownership (UK MNEs, foreign MNEs), whether the firm is multi-plant or not, λ_I and λ_R are industry and region dummies and the numbered subscripts 00 and 96 refer to the years 2000 and 1996. The results are set out in Table 3, where the first three columns are levels and the last three differences. Column 1 enters current *ln(Y/L)* on current *X*, and shows a 25% export productivity premium, similar to other studies.[7] To examine selection, column 2 reports the coefficient on a regression of current exporting on $ln(Y/L)_{t-2}$ 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 current *ln(Y/L)* on X_{t-2}, and shows that exporters are more productive two years later.

Turning to the differenced results, 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 which can be written

[7] It is interesting to compare these results with Kneller and Greenaway (2005) who use accounting data from OneSource and FAME datasets (11,225 firms, 1989-2002). They 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 (1990, table 1) who report 17% for 1992.

$$\begin{aligned} &Reference\ group: \quad X_t = 0, X_{t-1} = 0 \qquad never\ exporting \\ &X_t - X_{t-1} = \begin{cases} X_t > 0, X_{t-1} = 0 & starters \\ X_t = 0, X_{t-1} > 0 & stoppers \\ X_t > 0, X_{t-1} > 0 & continuers \end{cases} \end{aligned} \tag{10}$$

which describes the reference group, firms who never export and firms who change their status. This latter group consist of firms starting exporting, stopping exporting and firms who continue exporting (the latter firms are a 1 in both periods according to our measure, and therefore 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). Column 5 looks at this effect and suggests that most of the effect comes from firms who start exporting. Finally, column 6 shows a first differenced equation using X_{t-6} as an instrument for X_{t-2}-X_{t-6}. This effect is statistically significant.

Thus this section suggests that our data find what others find, namely a reduced form statistically significant relation between exporting and, periods later, productivity. This result mainly driven by new exporters (see also Fernandes and Isgut, 2005 for a discussion on learning by exporting). The following sections try to see if there is any support for the learning-by-exporting hypothesis that underlies this reduced form.

4.2 Learning results

Our estimating equation for learning is

$$(L^{BUYER} - L^{*})_{i,00/98} = \beta_1 X_{i,96} + \sum_{j=2}^{k} \beta_j D_{jit} + \lambda_I + \lambda_R + \varepsilon_{it} \tag{11}$$

where the numbers denote the time and 00/98 (and 96/94) refer to learning over that period. The following points are worth noting. First, on the left-hand side of (11), we use deviations from the mean of the other learning variables to try to control for changes in unobservables that might affect learning from various sources. Second, in some of the regressions, we also first difference to remove firm- fixed effects that are specific to learning from clients but not to other sources of learning (and use industry and region dummies to capture any other effects). Third, the export term in 96 is dated before the learning period 00/98 to try to help with endogeneity concerns.

When we difference (11), we do not have exporting in 92 to predate the 96/94 period and so are forced to use $X_{i,\,94}$.

In (11) the dependent variable is a (0/1) dummy. We constructed the dummy by first computing the average of all the different sources of learning (excluding buyers) using the original Likert scale (0-3). Then we coded learning from buyers as 1 if its scale was higher than the average. Concerning estimation method, since L^{BUYER}-$L*$ is a 1/0 variable in (11) we should estimate it using a discrete response models. 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[8]. A LPM also makes first differencing straightforward.

Table 4 sets out the estimates of (11). Column 1 shows results with X 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. There is no remotely significant relation suggesting that it is not the case that firms who export, were, in previous periods, learning more from clients. Interestingly, this differs from the common finding that firms are highly productive *before* they export, see above, and suggests that there are no reverse causality issues in the relation of exporting with learning. Column 3 enters lagged exports, again in levels, and finds a significant relation, suggesting that previous exporting is associated with current learning from clients. This is in line with the view that exporting implies more learning. Column 4 is a first differenced version of column 3 and shows the relationship weakening in significance but the coefficient being very similar to that found in column 3. To explore the differences in exports effect more, column 5 shows the coefficients associated with starters, stoppers and continuers. The interesting finding is that starters appear to exert the most statistically significant effects, in line with the results from the reduced form presented in Table 3.

Columns 6 to 11 checks whether our findings regarding L^{BUYER}-$L*$ are spurious by constructing deviations from the average of other learning types.[9] As the table shows, neither the correlations in levels (columns 6 to 8) or in differences (columns 9 to 11) are statistically significant at conventional levels.

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[8] The average of learning from clients in roughly 0.50 in both waves of the survey.

[9] For brevity, we only show the results for three cases learning from suppliers, competitors and trade associations, the results for the remaining ones were similar and are available upon request.

In summary, the table has looked at the deviation of learning from buyers from average learning from other sources. Our levels results suggest that firms who export report, two years later, statistically significantly more learning from buyers relative to other learning sources but no statistically significantly more learning from other sources, our difference results suggest that firms who change their exporting status, to become new exporters, report, two years later, increased learning from buyers relative to other learning sources (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

$$(Y/L)_{i,00} - (Y/L)_{i,96} = \gamma_1 (L^{BUYERS} - L^{*})_{i,96/94} + \gamma_2 L^{*}_{i,96/94} + \sum_{j=2}^{k} \gamma_j D_{jit} + \lambda_I + \lambda_R + \varepsilon_{it} \qquad (12)$$

where 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. The results of estimating (12) are set out in Table 5. Columns 1 shows the estimate of (12), omitting, for the moment, L^{*}, measured independently. The effect of L^{BUYERS}-$L*$ is statistically significant. Column 2 includes $L*$ and whilst the precision of L^{BUYERS}-$L*$ falls, it is still significant at the 10% level. Finally, column 3 enters L^{BUYERS} and $L*$ separately, but uses L^{BUYERS}-$L*$ as in instrument for L^{BUYERS}; again the L^{BUYERS} effect is statistically significant.

Thus these results suggest that firms who report more learning from buyers, relative to other forms of learning, are statistically significantly more likely to experience increases in labour productivity 2 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 and productivity. 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 and patterns 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 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 differences, past exporting is associated with statistically significantly more learning from buyers (relative to other sources), in line with the learning-by-exporting hypothesis. 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 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 more productivity. 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 TPF and labour productivity growth.

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 LPG, as we have shown here, or TFPG, further investigation would have to establish if exporting of one firm might affect TFPG 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.

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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
turn (£000)	3120	52533.89	537257.70
Employ	3120	271.31	824.45
LP (£000)	2962	112.17	240.58
US_MNE	3120	0.04	0.19
NOUS_MNE	3120	0.09	0.29
UK_MNEx	3120	0.10	0.29
Multiplant	3120	0.42	0.49
Information Sources			
Internal	3120	0.63	0.48
Clients	3120	0.64	0.48

Note: CIS2 and CIS3. Other learning variables not shown for brevity.

Table 2: Transition Matrix for exporters between 1996 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 growth and exporting
(regression esitimates of (9))

Labour Productivity	Column 1 Contemp Levels YL(i,t)	Column 2 Before Levels YL(i,t-2)	Column 3 After Levels YL(i,t)	Column 4 After FD [YL(i,t)-YL(i,t-4)]	Column 5 After FD,status [YL(i,t)-YL(i,t-4)]	Column 6 After FD,IV [YL(i,t)-YL(i,t-4)]
X(i,t)	0.2357	0.2415				
	[6.32]***	[4.14]***				
X(i,t-2)			0.2473			
			[5.75]***			
[X(i,t-2)-X(i,t-6)]				0.1177		0.225
				[1.67]*		[2.02]**
X(i,t-2)>0,X(i,t-6)=0					0.1586	
					[1.53]	
X(i,t-2)=0,X(i,t-6)>0					-0.0037	
					[0.04]	
X(i,t-2)>0,X(i,t-6)>0					-0.0718	
					[1.15]	
Constant	3.4575	3.5558	3.562	-0.7596	-0.7083	-0.7436
	[16.30]***	[13.31]***	[16.07]***	[1.49]	[1.34]	[1.45]
Observations	2147	1027	1408	738	656	738
R-squared	0.30	0.30	0.32	0.09	0.10	0.08

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. Labour productivity is computed as turnover over employment (headcount) and the growth rate is over a two years period. Robust t-test in parenthesis. In column (2) sample is restricted to all firm that did not exported in 1994 (t-6) and 1996 (t-4). Some of them did start exporting in 1998 (t-2) or 2000 (t).

Table 4: Exporting and learning (all learning variables are in deviation from the average form), estimates of (11)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Learning	Contemp Levels	Before Levels	After Levels	After FD	After FD,Status	After Levels	After Levels	After Levels	After FD	After FD
From	Learn(i,t) Clients	Learn(i,t-4) | Learn(i,t-6) Clients	Learn(i,t) Clients	Learn(i,t)-Learn(i,t-4) Clients	Learn(i,t)-Learn(i,t-4) Clients	Learn(i,t) Suppliers	Learn(i,t) Competitors	Learn(i,t) Trade Assoc	Learn(i,t)-Learn(i,t-4) Suppliers	Learn(i,t)-Learn(i,t-4) Competitors
X(it)	0.1171									
	[3.53]***									
[X(i,t)>0 | X(i,t-2)>0]		-0.0226								
		[0.32]								
X(i,t-2)			0.0888			0.0545	0.0191	0.047		
			[2.65]***			[1.52]	[0.54]	[1.57]		
[X(i,t-2)-X(i,t-6)]				0.0981					-0.0081	0.0158
				[1.51]					[0.14]	[0.25]
X(i,t-2)>0,X(i,t-6)=0					0.1308					
					[1.40]					
X(i,t-2)=0,X(i,t-6)>0					-0.0961					
					[0.77]					
X(i,t-2)>0,X(i,t-6)>0					0.0726					
					[0.97]					
Constant	0.1633	-0.2492	0.1683	0.1984	0.2437	0.3202	0.1408	0.1927	-0.1174	0.1546
	[1.10]	[1.02]	[1.13]	[0.68]	[0.83]	[1.99]**	[0.90]	[1.44]	[0.46]	[0.55]
Observations	1418	403	1418	749	749	1418	1418	1418	749	749

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. In all the regressions the dependent variable is some sort of learning "relative" to the average of the remaining sources. Robust t-test.. In column (2) sample is restricted to all firm that did not exported in 1994 (t-6) and 1996 (t-4). Some of them did start exporting in 1998 (t-2) or 2000 (t).

Table 5: Learning and labour productivity growth
(regression estimates of (12))

	Column 1 FD, OLS [YL(i,t)-YL(i,t-4)]	Column 2 FD, OLS [YL(i,t)-YL(i,t-4)]	Column 3 FD, IV [YL(i,t)-YL(i,t-4)]
(L(BUYER)-L*)(i,t-4)	0.0919	0.0701	0.0786
	[2.50]**	[1.84]*	[1.78]*
L*(i,t-4)		0.0575	0.0588
		[1.84]*	[1.95]*
Constant	-0.0465	-0.0367	-0.0447
	[0.37]	[0.29]	[0.35]
Observations	755	755	755
R-squared	0.07	0.08	0.08

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 t-test.

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