Learning-by-Exporting? Firm-Level Evidence for UK Manufacturing and Services Sectors*

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Abstract

This study empirically assesses the microeconomic exporting-productivity nexus for both the UK manufacturing and services sectors during 1996-2004, based on a weighted *FAME* dataset. Our results show that firms that are older, that possess intangible assets or that have higher (labour) productivity in the year prior to exporting, are significantly more likely to sell overseas. In testing the post-entry 'learning-by-exporting' effect, we employ three approaches to controlling for endogeneity and sample selection, viz. instrumental variables, control function and matching, and find that this effect is present in many industries but not universal, and also varies amongst different types of exporting firms. Our overall estimate for the UK economy suggests a substantial post-entry productivity effect for firms new to exporting; a negative effect for firms exiting overseas markets; and large productivity gains while exporting for those that both enter and exit.

JEL codes: D24; F14; L25; R38

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I. Introduction

The micro literature on globalisation suggests a number of ways whereby business internationalisation (i.e. successful exploitation of overseas markets) can contribute to growth and development for the firm and to productivity growth at the aggregate level. For instance, firms that internationalise have to overcome barriers to exporting (sunk costs), and therefore invest in resources and capabilities (i.e. absorptive capacity) that provide them with the ability to compete effectively in overseas markets. Thus they achieve higher productivity levels as a prelude to exporting (or other means of their international expansion). Consequently, there is a self-selection process whereby firms that enter export markets do so because they have higher productivity prior to entry[4]. This then raises the issue of whether exporting itself leads to further benefits through "learning" in global markets. The empirical evidence found for many countries provides significant support for the 'self-selection' hypothesis but much less support for the 'learning-by exporting' hypothesis (see Greenaway and Kneller, 2005, Table 1, for a summary of the evidence).

The contribution of exporting to productivity growth is important for policy. For instance, substantial evidence of the benefits from international trade provides the UK government with a rationale for intervention to help firms develop their exporting activities when there are market failures (DTI, 2006). These benefits are largely linked to the higher productivity of exporters, which then contribute to overall UK productivity growth through various channels, such as the entry of higher productivity exporters (e.g. the so-called 'born global' companies; see Oviatt and McDougal, 1995); existing exporters becoming more productive over time and/or leading intra-

[4] See Section II for a review of this hypothesis of self-selection.

industry resources to be reallocated to higher productivity exporters; and the shutdown of lower productivity firms - both exporters and more likely non-exporters with the lowest productivity level, as predicted by some recent theoretical models (Bernard *et. al.*, 2003; Melitz, 2003).

Nevertheless, there has to date been little micro-based evidence for the UK that quantifies the importance and contribution of exporting to overall UK productivity growth and thus substantiates these associated benefits. This paucity of UK evidence on the causes and impact of internationalisation can largely be explained by data limitations, owing to the lack of any information about export activities in the Annual Respondents Database (*ARD*) - the primary source of micro data collected by the Office for National Statistics (c.f. Harris, 2005). There have been a limited number of studies for the UK that have considered both whether exporters are 'better' than non-exporters, and whether there is any post-entry productivity improvement to exporters (e.g. Girma *et. al.*, 2004; Greenaway and Kneller, 2004; Greenaway and Yu, 2004). These analyses have used data from the *FAME* and *OneSource* databases based on returns firms have to make to Companies House in the UK, but there are a number of issues that arise from the use of these data, principally that the samples used in statistical analysis are not representative of the UK population of firms and as a result large firms are over-sampled.[5]

Thus the scope of the current study is to use appropriate micro data sources for the UK to assess the extent to which productivity growth within firms may be stimulated

[5] The *FAME* and *OneSource* databases are not based on samples drawn from the population of firms in production in the UK (since only firms above a certain size have to make returns with data that are then used in statistical analyses), and thus they contain no information on the UK population of enterprises. Meanwhile, as these sources are based on accounting definitions of variables, they do not always relate to the definitions assumed when estimating economic relationships, such as the production function. There are also issues concerning how well entry and exit are captured in these data. All of these points are returned to later in Sections III and IV.

by exporting, either through organisational learning or economies of scale. Therefore, we provide estimates for the whole of the market-based economy (both manufacturing and services) to consider: i) the extent to which exporters have higher total factor productivity (TFP), when compared to non-exporters; ii) whether exporters are more productive prior to entry into overseas markets and/or whether post-entry there is also a 'learning-by-exporting' effect.

We use a weighted *FAME* database to obtain a distribution representative of the population of firms operating in the UK. The weights are obtained from the *ARD* (at the level of 3-digit industry SIC by 5 size bands), as the *FAME* database is unrepresentative of small- to medium-sized enterprises and therefore cannot produce results that can be generalised to the UK level. In particular, our main results for firms in 16 separate UK industry groups (covering 1996-2004) confirm that in general exporters have higher productivity relative to non-exporters: in the year prior to selling in overseas markets, firms that export are older; have higher (labour) productivity; and exploit intangible assets. In testing the 'learning-by-exporting' effect, we find that post-entry productivity gains are present but by no means universal (even within industry groups there are differences amongst export entrants, exitors, and those that experience both entry and exit). Nevertheless, in terms of the overall estimate for the UK economy the results show that there is a fairly substantial post-entry productivity effect.

Thus our results confirm the predictions from the international entrepreneurship literature (see Harris and Li, 2005, for a review): no matter whether the traditional, incremental models of internationalisation, transaction cost models, or monopolistic advantage models are considered, a strong overlapping feature is the role and importance of firm specific assets (i.e. absorptive capacity) and knowledge accumulation.[6]

The rest of the paper is structured as follows. In Section II, we begin with an overview of the literature. In Section III we describe the weighted *FAME* dataset used for this study and highlight some data issues. This is then followed by a discussion of the methodological issues in estimation and our modelling strategies (Section IV) as well as the results from our econometric modelling (Section V). The last section concludes with some relevant implications for policymaking.

II. Exports and Productivity: Overview of the Literature

In recent years there has been a surge of interest in studying the microeconomic evidence of international trade, leading to a rapidly growing body of literature focusing on exporting and its impact on firms (e.g. productivity/performance improvement), taking into account the importance of heterogeneity amongst firms. This emphasis on firm-level evidence has been partly triggered by the availability of quality micro data, as well as recent developments in theoretical modelling and econometric techniques to exploit these usually more intricate micro datasets.

Research on the exporting-productivity nexus is generally empirically driven and it is mostly found in the literature that exporting is positively associated with firm performance.[7] Nevertheless, despite this positive linkage, there is still much controversy about whether causality runs from exporting to productivity, the other

[6] In previous work (Harris and Li, 2006), we find evidence that such assets and capabilities have a large impact on breaking down barriers to exporting for UK establishments, with these resources proxied by establishment (and firm) size, absorptive capacity, R&D activity, and cooperation with overseas organisations, etc.

[7] See Greenaway and Kneller (2004) for a recent survey.

way around or in both directions (i.e. a feedback relationship). These issues are often examined empirically by testing two competing hypotheses, viz. self-selection and learning-by-exporting.

The self-selection hypothesis assumes that firms that enter export markets do so because they have higher productivity prior to entry, relative to non-entrants. Underlying this selection effect is substantial evidence of differences between those that participate in export markets and those that do not. The general consensus based on evidence from a number of countries is that exporters are, on average, bigger, more productive, more capital intensive and pay higher wages vis-à-vis non-exporters (Baldwin and Gu, 2004; Girma *et. al.*, 2004; Greenaway and Kneller, 2004). The reasons for export-oriented firms to exhibit better performance are intuitively appealing: since increasing international exposure brings about more intensive competition, firms that internationalise are forced to become more efficient so as to enhance their survival characteristics; meanwhile, the existence of sunk entry costs means exporters have to be more productive to overcome such fixed costs before they can realise expected profits.

The literature on whether firms that export 'self-select' into overseas markets provides strong evidence that this is indeed the case. Theoretical models developed by Clerides *et. al.* (1998), Bernard *et. al.* (2003) and Melitz (2003) consider exporting firms needing to be more productive prior to overseas entry in order to overcome the fixed (sunk) costs of entering export markets. Lopez (2004) also develops a simple model in which forward-looking firms need to invest in new technology in order to become exporters, with the adoption of this technology requiring them to be more productive to begin with (so as to have the resources – or absorptive capacity – that allow them to learn and internalise the new knowledge). The empirical literature on self-selection of exporters has been recently surveyed by Greenaway and Kneller (2005) and Wagner (2005). In more than 30 studies reviewed in Greenaway and Kneller (*op. cit*.), covering a wide range of countries, 'self-selection' is universally found to be important.[8] Nevertheless, there are still some studies which find exporters are not more efficient than non-exporters: for instance, Bleaney and Wakelin (2002) with regard to UK manufacturing when controlling for innovating activity; Greenaway *et. al.* (2005) for Swedish manufacturers with a relatively high level of international exposure on average; and Damijan *et. al.* (2005) on firms in Slovenia where higher productivity is required only in those that export to advanced countries but not those who export to developing nations.

In addition, export-oriented firms are also assumed to experience an acceleration in productivity growth following entry, under the learning-by-exporting hypothesis. This proposition has received somewhat less support in the literature. Many early empirical studies raise doubts about the causality running from exporting to productivity, since they fail to find gains in productivity growth post entry, notwithstanding that exporting firms on average experience significantly higher growth in terms of employment and wages (Aw and Hwang, 1995; Bernard and Wagner, 1997; Bernard and Jensen, 1999; Delgado *et. al.*, 2002).

Nevertheless, much of the literature on international entrepreneurship emphasizes the importance of exporting as a learning process, consistent with the notion of absorptive capacity and the resource-based view of the firm (Cohen and Levinthal, 1989, 1990; Barney, 1991; Teece *et. al.,* 1997). The process of going international is perceived as a sequence of stages in the firm's growth trajectory, which involves substantial

[8] See Aw and Hwang (1995) for Taiwan; Bernard and Wagner (1997) for Germany; Clerides *et. al.* (1998) for Colombia; Mexico and Morocco; Bernard and Jensen (1999) for the US; Kraay (1999) for China; Alvarez (2001) for Chile; Castellani (2002) for Italy; Delgado *et. al.* (2002) for Spain; and Greenaway and Kneller (2004) for the UK.

learning through internal and external channels, so as to enhance its competency base and performance. Thus, the learning-by-exporting proposition is consistent with this literature on business internationalisation. Indeed, positive learning effects for firms engaged in exporting have been identified, particularly where different econometric methodologies are adopted (e.g. Kraay, 1999; Castellani, 2002; and Hallward-Driemeier *et. al.,* 2002). What is more, a strand of the literature also documents evidence on the co-existence of selection and learning effects, such as Baldwin and Gu (2003), Girma *et. al.* (2004) and Greenaway and Yu (2004).

Arguably the empirical evidence still remains inconclusive with respect to the causal mechanisms underlying the well-established empirical association between export orientation and productivity growth, in particular whether the learning-by-exporting hypothesis holds. Nevertheless, there may be several explanations to account for such discrepancies amongst the empirical literature in this area. Above all, there are structural differences between various databases used when testing for learning effects. For instance, in explaining distinct learning effects in Canadian and American plants, Baldwin and Gu (2004) put forward the following factors that might lead to more effective learning activities in Canadian plants: a smaller market size with less intense competition; benefits from greater product specialisation and longer production runs when expanding into much larger foreign markets relative to the domestic market, and relative importance of learning from international best practices to productivity growth, as the principal source of raising productivity in the US is technology developed domestically.

Secondly, the heterogeneity of export markets may also play a role in determining the extent to which participants will gain higher productivity from exporting. For instance, Damijan *et. al.* (2005) suggest that exporting *per se* does not warranty productivity gains; rather, productivity only improves significantly when firms are serving advanced, high-wage export markets. Lastly and most importantly, there are also crucial methodological issues involved when testing for a productivity effect from exporting. A problem usually encountered in microeconometric evaluation studies is sample selectivity. This arises when making comparisons between a 'treatment group' (e.g. export-market entrants) and the rest of the population, when it is suspected that the treatment group are not randomly drawn from the whole population. This issue is of paramount importance when interpreting the results obtained from comparing exporters and non-exporters, upon which policy conclusions are then based (see Section IV for more details; also Blundell *et. al.,* 2005, for a recent overview).[9,10] Several standard approaches have been proposed in the literature to combat this selection problem, such as 'matching' techniques to select a valid 'control' group to compare the performance of exporters with only those non-exporters with similar characteristics (Girma *et. al.*, 2004); and the difference-in-difference estimator to eliminate selectivity bias (Greenaway and Kneller, 2004).

III. Data and Descriptive Statistics

The *FAME* dataset is used for this study, which includes all firms operating in the UK that are required to make a return to Companies House. It contains basic information on firm-specific characteristics, such as turnover, intermediate expenditure, employment, assets, and most importantly, overseas sales. Apart from financial

[9] See Section IV for more details; also Blundell *et. al.* (2005) for a recent overview.
[10] Another potential econometric problem may arise since most empirical studies tend to pool information across all firms with heterogeneous export histories to examine these learning effects of exporting. In fact, distinct learning effects are uncovered amid firms of different ages (Kraay, 1999; Delgado *et. al.*, 2002; Baldwin and Gu, 2003; Greenaway and Yu, 2004).

information, *FAME* also has information on the year of incorporation of the company, postcodes, the 4-digit 2003 SIC industry code, and country of ownership. The definitions of variables included in our econometric models are provided in Table A1 in the Data Appendix. Note, we only use data containing unconsolidated accounts, to avoid double counting and within firm transfer effects. Our final dataset used for statistical analysis comprises of an unbalanced panel, containing 81,819 firms with 326,906 observations covering 1996-2004, where information on 'entry and exits' into export markets is also available.[11]

The *FAME* dataset is severely biased towards large enterprises, and thus is unrepresentative of UK firms. To obtain a distribution representative of the population of firms operating in the UK, we treat the firms in the *FAME* dataset as a sample of the *ARD* population[12], and consequently weight the *FAME* data to produce a representative database (by industry and firm size).[13] In practice, we have obtained aggregated turnover data from the *ARD* sub-divided into 5 size-bands (based on turnover quintiles) and 3-digit industry SICs[14]. We then aggregate the *FAME* data into the same sub-groups, so that we can calculate weights using the total turnover data from the *ARD* divided by the comparable data from *FAME*. In essence, the *FAME* dataset is weighted to acquire the same distribution of turnover as those firms in the *ARD*.[15]

[11] Nearly 23% of firms are observed throughout the nine-year period; thus the majority of firms are observed for only some of 1996-2004.
[12] For a details description of the *ARD* (available at the ONS), see Oulton (1997), Griffith (1999) and Harris (2005).
[13] Efforts have also been made to merge *FAME* into the *ARD*; nevertheless, these have been largely unsuccessful (see Harris and Li, 2007, Chapter 2, for more details).
[14] Where there are fewer than 10 enterprises in any sub-group, these data are not used, so as to avoid disclosure of confidential information in these ONS data. This results in a loss of some 4% of the total turnover available in the *ARD*.
[15] Note we do not weight the *FAME* data for 34 industries because the *FAME* data have better coverage in terms of total turnover than the *ARD*. These 34 industries (out of 215 in total) account for just 2.9%

Table 1: GB[a] turnover (£m) in 2003 based on *FAME* and *ARD* by size-bands

Size-band[b]	*FAME* Unweighted	%	*FAME* Weighted	%	*ARD*	%	*FAME* / *ARD*
	(1)		(2)		(3)		(2) ÷ (3)
<44	26.9	0.0	460.1	0.0	509.7	0.0	90.0
44 to 227	380.7	0.0	7,969.6	0.7	8,509.4	0.8	93.5
>227 to 1184	3,578.5	0.2	60,892.8	5.3	63,751.8	5.9	95.5
>1184 to 7244	49,683.9	2.4	198,417.1	17.4	200,988.3	18.5	98.7
>7244	1,988,609.3	97.4	874,543.9	76.5	812,157.0	74.8	107.5
All	2,042,279.4	100.0	1,142,283.4	100.0	1,085,916.2	100.0	105.0

[a] Unweighted *FAME* data covers the UK [b] Size-bands are in £'000 Source: *ARD* and *FAME* databases

Table 1 presents the results from weighting the *FAME* data. The unweighted data from *FAME* are dominated by the largest firms (defined as firms with turnover of £7.2 million or above) since this sub-group accounts for over 97% of total turnover. Weighting the *FAME* produces a distribution across size-bands that is comparable to that obtained when using the *ARD*. This is confirmed in the final column in Table 1, which shows that the ratio of *FAME* to *ARD* turnover by size-band is within a margin of ±10%. There is a suggestion that even weighted, the *FAME* data slightly underestimates the contribution of the smallest firms (and correspondingly overestimates the importance of the largest firms), but these differences are not likely to unduly impact on any statistical analysis undertaken using these weighted data.[16] All the subsequent statistical analyses are based on this weighted *FAME* dataset.

of total *FAME* turnover. Note also, the *ARD* does not contain data for Northern Ireland but since this region is rather small it will not have much of an effect in the weights used.

[16] We have also undertaken a further check of the usefulness of the weighted data on exports information (other than just turnover) by comparing it to information from the 2004 Community Innovation Survey (*CIS4*) that contains information on which establishments exported in 2004. Our findings suggest that while there are differences across industries, the relative magnitudes of the estimates of the percentage of firms that export for the two datasets are very similar. See Harris and Li (2007) for details.

Table 2: Two-sample Kolmogorov-Smirnov tests on the distribution of TFP by various sub-groups [a] and industries, UK 1996-2004

Industry (SIC2003 group)		Difference favourable to: All exporters vs.	All non-exporters	Difference favourable to: All permanent Exporters vs.	All never exported	Difference favourable to: All foreign-owned vs.	UK-owned non-exporters	Difference favourable to: All foreign-owned vs.	UK-owned Exporters	Difference favourable to: FO exporters vs.	FO non-exporters
Agriculture/Forestry/Fish (A/B)	**AGF**	-0.049	0.155**	-0.049	0.154**	-0.042	0.188**	-0.006	0.075	-0.328**	0.002
Food/Beverages/Tobacco (DA)	**FBT**	-0.001	0.241**	-0.001	0.259**	-0.002	0.329**	-0.014	0.095**	-0.029	0.206**
Textiles/Cloth/Leather (DB/DC)	**TCL**	-0.001	0.252**	-0.001	0.267**	-0.001	0.338**	-0.005	0.112**	-0.297**	0.094
Wood products (DD)		-0.004	0.312**	-0.001	0.351**	0.000	0.508**	0.000	0.297**	-0.182	0.610**
Paper/Printing (DE)	**WPP**	-0.004	0.255**	-0.006	0.273**	-0.001	0.262**	-0.030	0.023	-0.031	0.275**
Coke/Chemicals (DF/DG)		-0.013	0.199**	-0.028	0.219**	-0.023	0.228**	-0.009	0.056**	-0.001	0.187**
Rubber/Plastics (DH)	**CRR**	-0.005	0.142**	-0.004	0.144**	-0.006	0.207**	-0.020	0.083**	-0.098	0.014*
Non-metal minerals (DI)		-0.028	0.157**	-0.023	0.169**	-0.039	0.185**	-0.133**	0.039	-0.004	0.196
Basic metals/fabricated (DJ)	**MET**	-0.002	0.230**	-0.002	0.237**	-0.005	0.365**	-0.007	0.204**	-0.034	0.172*
Fabricated metals (DJ pt)		-0.008	0.215**	-0.005	0.240**	-0.012	0.279**	-0.014	0.074**	-0.018	0.120**
Machinery/Equipment (DK)		-0.002	0.199**	-0.000	0.208**	0.000	0.232**	-0.034	0.018	-0.003	0.105*
Office equip/Radio, TV (DI pt)		-0.026	0.177**	-0.037	0.161**	-0.009	0.195**	-0.048*	0.019	-0.128**	0.058
Electrical machinery (DI pt)		-0.039	0.264**	-0.041	0.316**	-0.041	0.280**	-0.030	0.022	-0.047	0.206**
Medical/Precision (DI pt)		-0.008	0.261**	-0.010	0.281**	-0.025	0.345**	-0.029	0.046	-0.002	0.245**
Motor vehicles/parts (DM pt)	**ENG**	-0.035	0.179**	-0.003	0.273**	-0.034	0.232**	-0.038	0.064	-0.097	0.071
Other transport (DM pt)		-0.033	0.245**	-0.038	0.301**	-0.050	0.321**	-0.109*	0.100	-0.060	0.367**
Manufacturing n.e.c. (DN)	**OMF**	-0.001	0.217**	-0.001	0.241**	0.000	0.278**	-0.011	0.070**	-0.019	0.135**
Construction (F)	**CON**	-0.008	0.262**	-0.010	0.289**	-0.002	0.234**	-0.066**	0.030	-0.027	0.090*
Repair/sale motors (G pt)	**RSM**	-0.002	0.213**	-0.002	0.228**	-0.001	0.337**	0.000	0.221**	-0.042	0.082
Wholesale trade (G pt)	**WHO**	-0.004	0.186**	-0.003	0.207**	0.000	0.211**	-0.020*	0.028**	-0.016	0.084**
Retail trade (G pt)	**RHR**	-0.001	0.292**	-0.001	0.316**	-0.001	0.328**	-0.038	0.057*	-0.052	0.097**
Hotels/restaurants (H)		-0.009	0.161**	-0.024	0.174**	-0.003	0.097**	-0.139**	0.091	-0.108	0.035
Transport services (I pt)		-0.011	0.276**	-0.015	0.285**	-0.001	0.250**	-0.110**	0.080**	-0.031	0.139**
Support for Transport (I pt)	**TRA**	-0.009	0.178**	-0.009	0.218**	-0.008	0.119**	-0.158**	0.007	-0.076	0.121**
Post/Telecoms (I pt)	**POT**	-0.011	0.151**	-0.011	0.144**	-0.008	0.099**	-0.090**	0.033	-0.024	0.154**
Financial intermediation (J)		-0.049**	0.220**	-0.060**	0.239**	-0.030*	0.201**	-0.037	0.037	-0.051	0.137**
Real estate (K pt)	**FIN**	-0.083**	0.149**	-0.091**	0.143**	-0.018	0.074**	-0.144**	0.148**	-0.156*	0.137*
Renting (K pt)		-0.017	0.317**	-0.016	0.358**	-0.060	0.126*	-0.239**	0.005	-0.024	0.427**
Computer services/R&D (K pt)		-0.001	0.142**	-0.001	0.160**	0.000	0.108**	-0.031*	0.024	-0.016	0.205**
Other Business services (K pt)	**BUS**	-0.023**	0.220**	-0.027**	0.238**	-0.022**	0.135**	-0.095**	0.019	-0.011	0.198**

Note: ** denotes null rejected at 1% level; * null rejected at 5% level. Source: calculations based on weighted *FAME*

[a] In each instance we are testing the two sub-groups listed against each other, with the null that the distribution of one sub-group dominates the other; the values measure the greatest difference between the two sub-groups, and a positive value means that a sub-group lies to the left of the opposing sub-group.

Next we follow a similar exercise to that used by Girma *et. al.* (2005) and Wagner (2006) to test the rank ordering of the TFP distribution of firms that differ in their involvement in international markets.[17] Calculating a two-sided Kolmogorov-Smirnov statistic, it is possible to test whether the productivity distribution of one sub-group of firms lies to the right of another sub-group. If so, there is shown to be first-order stochastic dominance between such variables.

Table 2 (the first two blocks of results) shows that firstly, in every industry examined firms that export have a distribution that lies significantly to the right of non-exporters.[18] We also look at the TFP levels for foreign-owned firms, comparing them to both UK exporters and non-exporters. As shown in the third and forth blocks of results, the distribution of TFP for foreign-owned subsidiaries dominates that of UK-owned non-exporters, but that foreign-owned firms are not always better than UK-owned exporters (UK-owned exporters unambiguously dominate foreign-owned firms in 10 out of the 30 industries examined). Lastly, the final set of results suggest that the TFP distributions of foreign-owned exporters are generally to the right of those of foreign-owned non-exporters in a majority of industry groups but not all.[19] Overall, this suggests that foreign-owned firms operating in the UK are less useful as a comparator sub-group when considering whether exporters have relatively higher productivity, since non-exporting foreign-owned firms have productivity advantages that do not necessarily stem from exporting to overseas markets (indeed FDI itself is an alternative means of internationalisation – see Head and Ries, 2003; Helpman *et.*

[17] See Section IV for details on the estimation of TFP.
[18] However, for three industries (financial intermediation; real estate; and other business services) it is also possible to reject the null that the distribution for exporters is more favourable. A closer examination shows that in these industries, exporters dominate non-exporters for a large part of the distribution of TFP values, but at some levels (usually at high levels of TFP) there is a cross-over and non-exporters dominate exporters.
[19] Our results therefore confirm those presented by Girma *et. al.* (*op. cit.*) that the productivity distribution of exporters dominate that of non-exporters in the UK (although we also cover non-manufacturing in this study).

al., 2004; and Girma, *et. al.*, 2005). Therefore we only include data on UK-owned firms in our subsequent analyses.

IV. Econometric Estimation Methods

To obtain estimate of total factor productivity (TFP), we firstly estimate an augmented production function as follows:

$$y_{it} = \alpha_0 + \alpha_E e_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \alpha_T t + \gamma X_{it} + \varepsilon_t \tag{1}$$

where y, e, m, and k refer to the logarithms of real gross output, employment, intermediate inputs and tangible assets in firm *i* in time *t*. We have also included a vector of variables, X, that determine TFP; hence TFP growth in this instance is defined as (dropping sub-scripts):

$$ln\dot{TFP} = \hat{\alpha}_T + \hat{\gamma}\dot{X} \equiv \dot{y} - \hat{\alpha}_E \dot{e} - \hat{\alpha}_M \dot{m} - \hat{\alpha}_K \dot{k} \tag{2}$$

Since the problem under consideration is to understand the causes of TFP (e.g. the role of exporting), the preferred approach to estimating TFP is to directly include the determinants of output (and thus TFP) into the production function, as this avoids any problems of statistical inefficiency and omitted variable bias associated with estimating a two-stage model using a growth accounting approach[20]. Moreover, this method also allows us to directly test whether such determinants are statistically significant.

In estimating models to determine the linkages between exporting and productivity using micro level data, the issues of primary concern are the problems of endogeneity

[20] Refer to Harris (2005) for a detailed discussion of the issues concerning the measurement of TFP, such as inefficient estimates (Newey and McFadden, 1999, Section 6), omitted variable problem (Wang and Schmidt, 2002) when using a two-stage model and the endogeneity of inputs and outputs in a production model.

and sample selection.[21] Briefly, in estimating the exporting-productivity relationship, selection bias occurs because participants in export markets may posses certain characteristics such that they would achieve better performance vis-à-vis non-participants even if they did not enter export markets, and this productivity gain is correlated with the decision to participate in the global market. This will mean that standard estimation techniques lead to biased results. Thus the essential problem at the core of evaluating the effect of exporting is to obtain an estimate of the unobserved counterfactual that is not biased because of any simultaneous relationship between the decision to export and the gains from exporting.

There are several approaches that attempt to eliminate the bias that arises from self-selection (cf. Blundell *et. al.*, 2005). The first considered here is matching. Essentially, this involves matching every exporting firm with another firm that has (very) similar characteristics but does not export. Essentially, under the matching assumption exporters and non-exporters have the same (observable) attributes that impact on productivity (and the probability of exporting). Thus the non-exporting, matched sub-group constitutes the correct counterfactual for the missing information on the outcomes that exporters would have experienced, on average, if they had not exported. There are a number of issues associated with the matching process, including the need for a rich dataset that includes all relevant variables that impact on productivity and all variables that impact on whether the firm exports or not. Matching is done on the set of selection criteria, so that any selection on unobservables is assumed to be trivial and does not affect outcomes in the absence of exporting.[22, 23] Here, we have adopted

[21] Standard evaluation problems are discussed in Heckman (2000), Moffitt (2004), and Heckman and Navarro-Lozano (2004).

[22] Typically firms that export which are not 'supported' by firms from the non-export population are dropped, which can reduce significantly the size of the export sub-group included in any analysis. So where there is little common support between the treated and non-treated comparators, matching breaks down.

[23] Another issue is that by definition, matching assumes that the effect for the average export firm is the same as the effect for the marginal firm (the 'treatment on the treated' effect equals the unconditional

the propensity score matching approach where we first estimate a model to identify the probability of exporting (i.e. the propensity score) using the following (random effects panel) probit model:

$$P\left(Export_{it}=1\right)=\phi\left(\ln LP_{it-1}, \ln Age_{it-1}, Intang_{it-1}, Size_{it-1}, Industry_{it,} Region_{it}\right) \quad (3)$$

where $Export$ is coded 1 if the firm exported at any time during 1996-2004; LP is labour productivity; Age is the age of the firm; $Intang$ is coded 1 if the firm has non-zero intangible assets[24]; $Size$ represents a set of dummy variables that indicate whether the firm belongs to one of the following 4 size bands: 10-19, 20-49, 50-199 or 200+ employees; and $Industry$ and $Region$ are dummy variables indicating each industry sub-group or Government Office region. Following Girma *et. al.* (2004), if P_i is the propensity score of exporting for firm *i* at time *t*, we then use the propensity score matching procedure available in STATA 9 to find the closest match (using the "nearest-neighbour" approach) for each exporting firm in terms of the propensity scores from the sub-group of non-exporting firms, i.e.:

$$\left|P_i - P_j\right| = \min_{k \notin \{Export_k = 0\}} \{P_i - P_j\} \quad (4)$$

Having obtained a matched sample, we estimate a multivariate model using the matched data to test the learning-by-exporting hypothesis. This combination of matching and parametric estimation is argued to improve the results obtained from non-experimental evaluation study (e.g. Blundell and Costa Dias, 2000), as other impacts on the outcome variable are explicitly controlled for.

average treatment effect). Heckman and Navarro-Lozano (2004) argue that this is an unattractive implication.

[24] Here these non-monetary assets usually refer to corporate intellectual property (e.g. patents, copyrights, trademarks, etc.), innovative activities, advertising, goodwill, brand recognition and similar intangible assets. There is sufficient ambiguity of exactly what should be included as intangible assets (and issues over how to measure such assets – see, for example, Webster and Jensen, 2006)) that we have chosen to use a dummy variable rather than the actual monetary amount reported in *FAME*.

A second approach to dealing with self-selection bias is instrumental variable (IV) estimation[25]. If a variable(s) can be found that affects whether a firm engages in exporting but does not affect outcomes directly then such a variable(s) can be used to instrument for the treatment and overcome the problem of self-selection. The main issue in practice is finding an appropriate instrument(s).

In terms of the data available in *FAME*, the likely candidates as instruments are the age of the firm and whether it possesses any intangible assets. Firm age is not usually included in the production function, as the capital stock is presumed to provide an adequate measure of the vintage of the assets used in production. As to intangible assets (such as R&D and advertising), we follow the standard approach in the IO literature and presume that most (sunk cost) investment in intangibles is to overcome existing barriers to entry into new markets (see Carlton, 2005). Thus intangible assets feature in Equation (3). Evidence in favour of this approach is based on estimating industry-level production functions, where we find that these variables are always statistically insignificant determinants of (real) gross output, having controlled for the other covariates in the model, but they are usually highly significant in determining whether the firm sells overseas. Consequently, we include the logarithms of age and a dummy variable to indicate whether intangible assets are possessed, as part of the instrument set when estimating the following dynamic panel-data model, allowing for an autoregressive error term:

$$\begin{aligned}\ln Y_{it} = \beta_0 &+ \sum_{j=1}^{4}\pi_{1j}x_{jit} + \sum_{j=1}^{4}\pi_{2j}x_{ji,t-1} + \sum_{l=1}^{4}\sum_{j=1}^{4}\pi_{3j}(D_l x_{jit}) + \pi_4 \ln Y_{i,t-1} \\ &+ \sum_{l=2}^{4}\sum_{s=-1}^{1}\gamma_s D_{li,t-s} + \sum_{l=1}^{4}\beta_l D_l + \sum_{n=1}^{11}\delta_n REG_n + \sum_{p=1}^{x}\tau_p IND_p \\ &+ \eta_i + t_t + (1-\rho)e_{it} \end{aligned} \qquad (5)$$

[25] To our knowledge, there are few studies utilising instrumental variable estimation to examine the causality between export and productivity, probably due to a lack of appropriate instruments.

where the subscripts i and t represent the i-th firm and the t-th year of observation, respectively; Y represents real gross output; x_1 represents the logarithm of intermediate inputs, m; x_2 represents the logarithm of capital stock, k; x_3 represents the logarithm of total employment, e; x_4 represents a time trend to take account of technical progress, t; D_l is a set of dummy variables indicating export status, including EXP_{never}, EXP_{entry}, EXP_{exit}, EXP_{both} [26]; REG_n and IND_p are region and industry dummies variables respectively; and the composite error term has three elements with η_i affecting all observations for the cross-section firm i; t_t affects all firms for time period t; and e_{it} affects only firm i during period t.[27] Note here we divide firms into 5 different sub-groups based on exporting status: those that always exported, those that never exported, those that entered into exporting, those that exited, and lastly, those that started and then stopped exporting more than once.

To allow for potential endogeneity of factor inputs and exporting, Equation (5) is estimated using the Generalised Method of Moments (GMM) systems approach available in STATA 9 (Arellano and Bond, 1998). This is sufficiently flexible to allow for both endogenous regressors (through the use of appropriate instruments involving lagged values – in both levels and first differences – of the potentially endogenous variables in the model) and a first-order autoregressive error term.

Thirdly, the standard Heckman two-stage (or control function) approach is a widely used approach to dealing with self-selection bias, which is closely linked to the IV approach. This approach begins with a first-stage use of a probit (or logit) estimator to

[26] Note, D_ι is a constant that defines each sub-group (the baseline group are those that always exported, i.e. EXP_{always}). However, for the last three sub-groups (ι=2, 3, 4) firm i switches into the sub-group at time t, and therefore we denote this by $D_{\iota it}$. The latter variable enters contemporaneously and with a lead and lagged term, to consider whether firms experience 'export-by-learning' effects with time lags.

[27] Note, if e_{it} is serially correlated such that $e_{it} = \rho e_{it-1} + u_{it}$ then u_{it} is uncorrelated with any other part of the model, and $|\rho|<1$ ensures the model converges to a long-run equilibrium (i.e. the variables in the model are cointegrated).

generate first-stage predicted values of the probability of exporting, with the second stage estimation of Equation (5) including the sample selectivity correction terms from the first-stage model. That is, if $\hat{P}_{it}$ is the predicted propensity score of exporting for firm *i* at time *t* (cf. Equation 3), then the inverse Mills ratios (or selectivity terms) from this model are give by:

$$\lambda_{0it} = \frac{-\phi(\hat{P}_{it})}{1 - \Phi(\hat{P}_{it})} \quad \mathit{if}\ \mathit{Export} = 0; \qquad \lambda_{1it} = \frac{\phi(\hat{P}_{it})}{\Phi(\hat{P}_{it})} \quad \mathit{if} \quad \mathit{Export} = 1 \tag{6}$$

These selectivity terms (λ_0 and λ_1) enter Equation (5) to control directly for the correlation of the error term in the model determining TFP with the error term in the model determining whether the firm exports or not.

Several authors (Puhani, 2000; Smith, 2004; Angrist and Krueger, 2001) point out the problems associated with the Heckman approach, such as the need for exclusion restrictions otherwise the model may only be identified through the nonlinearity of the selectivity parameter included in the second stage equation. In summary, we choose to test for the relationship between exporting and productivity using all three approaches, viz. an IV approach, a control function approach, and a matching approach.

V. Empirical Modelling and Results

To examine the self-selection hypothesis, we estimate Equation (3) using weighted *FAME* data, in a probit model to determine which firms exported at any time during 1996-2004. Because of space constraints, the results for 16 industry sub-groups are not reported here but are available from the authors.[28] Our estimation results show that larger firms are much more likely to engage in exporting; and firms with higher

[28] See http://www.gla.ac.uk/departments/economics/staff/pdfs/Table_S1.pdf

(labour) productivity[29] in period $t-1$ are significantly more likely to sell overseas in period *t*, although the strength of this relationship varies across industry sub-groups. Generally, the impact of productivity on the probability of exporting is larger in the manufacturing sector.

Firms with non-zero intangible assets are also generally much more likely to export, and this again points to a need to invest in highly productive resources that lead to a greater ability to internalise external knowledge in order to overcome barriers to exporting (the absorptive capacity argument). The average effect across all the industry sub-groups suggests that having intangible assets increases the likelihood of exporting by some 7%; however, in some industries (e.g. food, beverages and tobacco; metals; and other manufacturing) the impact is much larger (around 19% on average), while in some industries there is no significant effect (covering repair/sale of motor vehicles; transport services; post/telecoms; and finance) or even a negative impact (in agriculture; and retail, hotels and restaurants). It is also worth noting that the age of the firm in *t-1* is usually found to be a major determinant of exporting, supporting process-based incremental models of internationalisation (cf. Johanson and Vahlne, 1977).

Thus, in line with the majority of previous studies, we also find that there was strong self-selection by UK firms during 1996-2004, in all of the 16 industry sub-groups examined. Turning to our results from estimating Equation (5) in order to test whether there is also a ‘learning-by-exporting’ effect associated with post-entry sales to overseas markets, we have employed the three approaches discussed above. As stated above, we include $ln\,Age_{it}$ and $Intang_{it}$ as part of the instrument set when estimating the production function, since we find that these variables are not significant

[29] Labour productivity (rather than TFP) is used in estimating the probability of exporting as we need the results from the probit model (i.e. the selectivity terms) when estimating the ‘control function’ production function model.

themselves when introduced as right-hand-side variables in (5) although they are generally important as prior determinants of the likelihood of exporting. Our second approach is to include the sample selectivity correction terms λ_0 and λ_1 in Equation (5) so as to control directly for the correlation between the error terms in Equations (3) and (5). This is labelled the 'control function' model in our results. Lastly, we use the propensity score matching procedure to obtain a matched sample of exporters and non-exporters based on Equation (4), and this matched sample is used when estimating Equation (5).

The full set of results from estimating Equation (5) are reported in Table 3, based on long-run estimates (but including the lagged coefficient on the dependent variable in order to assess how long it takes to converge on the long-run equilibrium reported) and diagnostic tests for each industry sub-group. In most cases, the models estimated are satisfactory in terms of autocorrelation (*cf*. the AR(1) and AR(2) test statistics) and the adequacy of the instrument set used (*cf*. the Hansen test results).[30] Here we concentrate on the variables linked to 'learning-by-exporting', but it is interesting to note that our results show that increasing returns-to-scale generally were present for all sub-groups (across the 16 industries examined, the average sum of the output elasticities was 1.14 for those firms that had always exported, followed by a value of 1.13 for those moving into exporting; the average RTS for firms never exporting was the lowest at 1.02).

[30] Similar results (in terms of diagnostic statistics and often parameter estimates) are obtained when the 'control function' model and the matching model are estimated. Detailed results for these two models are not reported in this paper but they are available upon request.

Table 3: Weighted systems GMM production function long-run estimates [a], UK 1996-2004 (Eq. 5)

Industries: / Independent variables:	AGF $\hat{\beta}$	AGF *t*-stat	FBT $\hat{\beta}$	FBT *t*-stat	TCL $\hat{\beta}$	TCL *t*-stat	WPP $\hat{\beta}$	WPP *t*-stat
ln gross output$_{t-1}$	0.191	1.84	0.062	0.74	0.230	2.69	0.159	1.46
ln M x EXP_always	1.010	4.13	0.686	4.36	0.848	6.90	0.803	4.01
ln M x EXP_never	0.423	5.15	0.696	21.05	0.433	18.71	0.606	5.03
ln M x EXP_entry	0.939	4.48	0.675	5.57	0.841	7.79	0.519	3.22
ln M x EXP_exit	0.523	1.98	0.874	12.77	0.635	8.75	0.539	3.31
ln M x EXP_both	1.142	1.94	0.553	7.92	0.804	7.27	0.488	3.65
ln K x EXP_always	0.102	2.14	0.113	3.32	0.119	2.41	0.151	2.61
ln K x EXP_never	0.155	2.52	0.170	4.01	0.179	3.03	0.245	2.78
ln K x EXP_entry	0.048	1.89	0.066	2.62	0.161	2.40	0.225	2.37
ln K x EXP_exit	0.420	1.90	0.112	1.89	0.142	2.36	0.269	2.14
ln K x EXP_both	0.106	1.06	0.272	3.96	0.144	1.83	0.248	2.74
ln E x EXP_always	0.049	2.87	0.268	2.55	0.160	2.23	0.148	3.06
ln E x EXP_never	0.200	3.00	0.216	4.53	0.189	2.64	0.296	3.54
ln E x EXP_entry	0.089	2.03	0.475	4.20	0.074	2.28	0.338	3.63
ln E x EXP_exit	0.150	2.77	0.130	4.92	0.190	2.67	0.218	1.93
ln E x EXP_both	0.188	2.98	0.207	3.10	0.095	1.92	0.296	2.95
t x EXP_both	0.134	3.07	0.039	2.20	0.004	0.25	0.030	1.56
t x EXP_never	0.016	1.54	0.006	1.08	0.004	0.18	0.004	0.53
t x EXP_entry	0.023	0.61	-0.014	-1.33	-0.023	-0.96	0.004	0.20
t x EXP_exit	0.013	0.12	0.026	1.17	0.039	0.61	0.025	1.15
t x EXP_always	-0.005	-0.38	0.006	1.12	-0.003	-0.44	-0.021	-1.08
EXP_entry $_{t+1}$	0.061	0.99	-0.013	-0.15	0.066	0.32	0.678	1.87
EXP_entry $_{t}$	-0.012	-0.16	0.117	2.31	0.173	0.81	-0.228	-0.52
EXP_entry $_{t-1}$	-0.066	-0.71	-0.019	-0.28	-0.094	-1.13	-0.238	-1.99
EXP_exit $_{t+1}$	0.084	0.67	-0.126	-1.83	-0.284	-1.83	0.107	0.38
EXP_exit $_{t}$	0.133	0.45	-0.054	-0.62	-0.072	-0.44	0.118	0.88
EXP_exit $_{t-1}$	-0.447	-0.53	-0.049	-1.23	0.157	1.31	-0.236	-1.64
EXP_both $_{t+1}$	0.689	4.66	-0.021	-0.30	-0.086	-1.10	0.076	0.91
EXP_both $_{t}$	0.042	0.33	0.211	2.08	-0.153	-1.57	-0.013	-0.15
EXP_both $_{t-1}$	0.260	1.42	-0.104	-1.80	0.110	0.94	0.057	1.09
Constant x EXP_always	1.281	1.05	2.344	2.75	-0.628	-0.85	1.548	0.68
Constant x EXP_never	1.122	0.89	-0.884	-1.07	2.535	3.31	-0.705	-0.31
Constant x EXP_entry	0.001	0.00	-0.261	-0.26	0.103	0.09	0.716	0.32
Constant x EXP_exit	0.272	0.07	-1.085	-1.36	1.427	1.49	0.249	0.11
Constant x EXP_both	-4.562	-0.73	-1.557	-1.96	0.500	0.45	1.793	0.71
Industry dummies	yes		yes		yes		yes	
Region dummies	yes		yes		yes		yes	
Diagnostic statistics								
No. of Obs.	1702		3065		2223		6903	
No. of groups	508		741		530		1798	
Hansen-test (χ^2)	107.15		185.96		150.91		265.83	
AR(1) z-statistic	-3.24***		0.095*		-2.29**		-2.91***	
AR(2) z-statistic	1.08		0.738		1.48		-0.76	

[a] The lagged coefficient on the dependent variable is also reported in order to assess its adjustment speed.

Notes: Refer to Table 2 for details of industry group codes. The 2-step GMM system estimator in STATA 9 is used; the instrument set includes lagged values of the RHS variables in the model as well as $ln\ Age_{it}$ and $Intang_{it}$. Standard errors are obtained using the 'delta' method.$^{***/**/*}$ significant at the 1%/5%/10% level.

Table 3 (cont.)

Industries: / Independent variables:	CRR $\hat{\beta}$	CRR *t*-stat	MET $\hat{\beta}$	MET *t*-stat	ENG $\hat{\beta}$	ENG *t*-stat	OMF $\hat{\beta}$	OMF *t*-stat
ln gross output$_{t-1}$	0.194	3.32	0.238	3.05	0.165	1.81	0.136	1.59
ln M x EXP_always	0.739	4.91	0.857	3.44	0.676	4.71	0.785	5.67
ln M x EXP_never	0.794	8.52	0.797	12.04	0.637	10.53	0.783	10.69
ln M x EXP_entry	0.779	5.18	0.827	12.17	0.805	15.15	0.907	21.24
ln M x EXP_exit	0.774	9.36	0.962	12.23	0.916	8.04	0.776	7.13
ln M x EXP_both	0.865	14.11	0.575	3.84	0.543	6.99	0.714	7.67
ln K x EXP_always	0.201	4.67	0.104	2.34	0.169	2.95	0.133	2.11
ln K x EXP_never	0.217	4.88	0.114	2.50	0.113	2.24	0.221	4.43
ln K x EXP_entry	0.116	5.30	0.045	1.85	0.051	2.20	0.127	2.43
ln K x EXP_exit	0.183	4.45	0.048	1.91	0.095	2.02	0.129	2.40
ln K x EXP_both	0.095	3.92	0.172	3.50	0.109	1.86	0.225	4.47
ln E x EXP_always	0.211	2.78	0.097	2.37	0.088	3.00	0.190	2.23
ln E x EXP_never	0.062	2.38	0.158	2.89	0.261	2.65	0.062	3.65
ln E x EXP_entry	0.320	5.31	0.242	3.58	0.283	4.34	0.166	2.96
ln E x EXP_exit	0.139	2.43	0.165	2.49	0.120	1.54	0.206	2.50
ln E x EXP_both	0.253	4.89	0.165	1.99	0.446	4.20	0.094	2.92
t x EXP_both	-0.011	-0.56	-0.042	-2.23	0.022	1.81	0.006	0.26
t x EXP_never	0.004	0.39	-0.005	-0.76	-0.009	-1.09	-0.036	-2.01
t x EXP_entry	-0.019	-0.63	0.017	1.40	0.002	0.14	-0.004	-0.31
t x EXP_exit	0.044	2.55	-0.010	-0.50	-0.006	-0.27	-0.002	-0.09
t x EXP_always	0.008	1.55	-0.002	-0.23	0.005	0.66	-0.007	-1.12
EXP_entry $_{t+1}$	0.242	1.58	-0.004	-0.06	0.112	1.50	-0.094	-1.02
EXP_entry $_{t}$	0.030	0.22	-0.043	-0.61	0.278	2.62	0.272	3.12
EXP_entry $_{t-1}$	0.068	1.29	-0.052	-0.84	-0.215	-2.01	-0.084	-1.80
EXP_exit $_{t+1}$	-0.186	-1.88	-0.264	-3.72	0.098	1.27	-0.068	-0.69
EXP_exit $_{t}$	-0.692	-3.26	0.120	1.30	-0.091	-0.73	0.094	0.70
EXP_exit $_{t-1}$	0.399	1.76	0.237	4.24	-0.114	-1.82	0.055	0.52
EXP_both $_{t+1}$	-0.025	-0.33	-0.072	-0.93	-0.048	-0.66	-0.045	-0.86
EXP_both $_{t}$	-0.004	-0.20	0.071	0.97	0.036	0.60	0.042	0.51
EXP_both $_{t-1}$	-0.017	-0.22	-0.008	-0.18	0.009	0.17	-0.055	-1.34
Constant x EXP_always	0.924	1.75	0.834	0.80	1.634	3.01	0.849	0.71
Constant x EXP_never	0.338	0.55	0.189	0.16	0.471	0.78	0.284	0.21
Constant x EXP_entry	0.147	0.20	0.399	0.37	-0.155	-0.24	-0.969	-0.83
Constant x EXP_exit	0.621	1.01	-0.020	-0.02	-0.756	-1.05	-0.081	-0.06
Constant x EXP_both	0.352	0.62	2.959	2.32	0.411	0.78	0.349	0.31
Industry dummies	yes		yes		yes		yes	
Region dummies	yes		yes		yes		yes	
Diagnostic statistics								
No. of Obs.	4629		7075		9596		3731	
No. of groups	1107		1719		2252		948	
Hansen-test (χ^2)	230.23		324.10		311.20		212.36	
AR(1) z-statistic	-1.95*		-2.69***		-2.77***		-1.23	
AR(2) z-statistic	0.49		-0.87		-1.16		-0.91	

Table 3 (cont.)

Independent variables: / Industries:	CON		RSM		WHO		RHR	
	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat
ln gross output$_{t-1}$	0.038	0.58	0.398	4.49	0.460	8.02	0.387	3.37
ln M x EXP_always	0.691	5.64	0.823	4.66	0.460	2.80	0.771	2.61
ln M x EXP_never	0.799	15.93	0.729	10.20	0.583	3.20	0.380	2.87
ln M x EXP_entry	0.898	19.43	0.914	31.09	0.459	5.45	0.633	4.68
ln M x EXP_exit	0.635	5.17	0.872	20.66	0.271	3.06	0.576	2.66
ln M x EXP_both	0.951	24.15	0.867	11.88	0.608	8.43	0.426	2.12
ln K x EXP_always	0.229	2.99	0.121	2.05	0.107	2.66	0.234	2.96
ln K x EXP_never	0.159	2.55	0.102	2.27	0.257	2.05	0.137	2.60
ln K x EXP_entry	0.124	2.05	0.073	2.05	0.071	2.67	0.102	2.39
ln K x EXP_exit	0.141	2.73	0.049	2.17	0.205	2.35	0.077	1.84
ln K x EXP_both	0.162	2.46	0.022	1.68	0.302	2.03	0.228	2.61
ln E x EXP_always	0.171	2.23	0.263	2.99	0.579	2.76	0.437	2.51
ln E x EXP_never	0.161	2.68	0.182	3.86	0.232	2.00	0.453	2.63
ln E x EXP_entry	0.119	2.22	0.058	2.03	0.598	3.43	0.539	2.80
ln E x EXP_exit	0.446	3.66	0.088	2.55	0.243	2.65	0.186	2.43
ln E x EXP_both	0.049	1.99	0.208	2.13	0.144	2.04	0.291	1.85
t x EXP_both	0.014	2.44	-0.001	-0.08	0.015	0.73	-0.006	-0.01
t x EXP_never	-0.004	-0.85	0.000	0.01	0.016	2.24	-0.023	-1.69
t x EXP_entry	0.008	0.38	-0.015	-0.54	0.181	1.95	0.022	0.52
t x EXP_exit	-0.044	-1.67	0.010	0.34	0.132	1.38	0.045	0.43
t x EXP_always	-0.021	-1.36	-0.004	-0.16	0.005	0.41	-0.021	-0.50
EXP_entry $_{t+1}$	0.069	1.34	0.051	0.76	-0.341	-0.91	-0.605	-2.18
EXP_entry $_{t}$	0.101	1.95	0.065	0.79	-0.376	-1.82	0.104	0.79
EXP_entry $_{t-1}$	-0.123	-1.59	0.019	0.29	-0.157	-0.67	-0.067	-0.39
EXP_exit $_{t+1}$	0.069	0.58	-0.446	-3.68	-0.426	-1.63	-0.111	-0.55
EXP_exit $_{t}$	-0.151	-1.12	0.048	0.51	0.000	0.00	-0.596	-0.64
EXP_exit $_{t-1}$	-0.004	-0.05	0.131	1.82	-0.375	-1.65	0.111	0.14
EXP_both $_{t+1}$	0.033	1.17	0.166	1.40	-0.213	-2.56	0.566	0.63
EXP_both $_{t}$	0.026	0.96	0.047	0.46	0.181	1.31	0.135	0.39
EXP_both $_{t-1}$	-0.010	-0.42	0.078	1.04	-0.132	-2.10	0.323	0.34
Constant x EXP_always	1.520	3.46	0.660	0.82	3.151	1.83	-0.273	-0.09
Constant x EXP_never	-0.180	-0.35	1.032	1.16	-0.684	-0.41	3.403	1.25
Constant x EXP_entry	-0.425	-0.54	0.213	0.25	-0.297	-0.17	2.282	0.70
Constant x EXP_exit	0.455	0.51	0.791	0.89	1.549	0.66	3.614	1.21
Constant x EXP_both	-1.090	-2.06	0.394	0.37	-0.337	-0.19	5.904	0.53
Industry dummies	yes		yes		yes		yes	
Region dummies	yes		yes		yes		yes	
Diagnostic statistics								
No. of Obs.	10531		6094		12753		10414	
No. of groups	3055		1644		3389		2978	
Hansen-test (χ^2)	295.22		167.54		374.03**		226.59	
AR(1) z-statistic	-2.74***		-2.05**		-3.69***		-4.02***	
AR(2) z-statistic	1.93*		-0.66		-3.69		1.46	

Table 3 (cont.)

Industries: / Independent variables:	TRA		POT		FIN		BUS	
	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat
ln gross output$_{t-1}$	0.467	3.22	0.225	2.70	0.631	5.20	0.416	6.59
ln M x EXP_always	0.878	2.94	0.716	5.07	0.932	4.40	0.759	3.87
ln M x EXP_never	0.609	9.33	0.769	14.76	0.453	6.66	0.846	7.63
ln M x EXP_entry	0.766	7.64	0.501	4.59	0.293	2.46	0.749	4.72
ln M x EXP_exit	0.698	8.91	0.415	2.75	0.430	2.69	0.560	2.62
ln M x EXP_both	0.252	2.37	0.124	2.56	0.187	1.93	0.468	2.51
ln K x EXP_always	0.132	2.35	0.119	2.35	0.090	2.14	0.171	2.34
ln K x EXP_never	0.071	2.04	0.138	2.34	0.096	2.55	0.025	2.28
ln K x EXP_entry	0.136	1.90	0.234	3.90	0.150	2.68	0.062	3.24
ln K x EXP_exit	0.126	1.82	0.106	2.11	0.304	3.27	0.165	1.63
ln K x EXP_both	0.042	1.61	0.249	1.88	0.160	1.88	0.219	2.44
ln E x EXP_always	0.209	2.83	0.339	2.63	0.244	2.44	0.122	2.31
ln E x EXP_never	0.198	2.41	0.134	2.41	0.440	2.94	0.298	2.85
ln E x EXP_entry	0.090	3.28	0.305	3.28	0.651	3.55	0.370	2.33
ln E x EXP_exit	0.148	3.55	0.776	4.55	0.363	2.00	0.411	2.34
ln E x EXP_both	0.410	3.51	0.641	2.81	0.677	3.61	0.396	2.17
t x EXP_both	-0.103	-0.78	0.016	0.17	0.036	0.72	0.025	0.62
t x EXP_never	0.007	1.02	-0.030	-1.50	-0.003	-0.56	-0.008	-0.54
t x EXP_entry	0.048	1.50	0.138	2.67	-0.010	-0.13	-0.048	-0.63
t x EXP_exit	0.046	1.88	0.098	0.47	-0.030	-0.40	-0.039	-0.94
t x EXP_always	-0.011	-0.34	-0.068	-1.27	-0.005	-0.30	0.010	0.44
EXP_entry $_{t+1}$	0.122	0.99	-0.001	0.00	-0.314	-1.48	-0.260	-0.44
EXP_entry $_{t}$	-0.025	-0.41	0.135	2.61	0.673	3.22	0.649	2.51
EXP_entry $_{t-1}$	-0.095	-0.95	0.047	0.40	0.106	0.46	-0.160	-0.45
EXP_exit $_{t+1}$	-0.247	-1.86	0.102	2.40	-0.267	-1.00	-0.049	-0.29
EXP_exit $_{t}$	0.033	0.24	-0.736	-2.24	0.115	0.35	0.442	0.87
EXP_exit $_{t-1}$	0.087	0.80	0.359	0.92	-0.012	-0.06	0.023	0.11
EXP_both $_{t+1}$	-0.277	-0.53	0.247	0.61	0.235	0.71	-0.434	-1.43
EXP_both $_{t}$	-0.291	-0.74	0.109	0.37	0.542	2.11	0.025	0.14
EXP_both $_{t-1}$	-0.051	-0.13	0.063	0.34	0.007	0.04	-0.284	-1.68
Constant x EXP_always	-0.856	-0.38	0.856	0.45	0.620	0.59	2.735	1.66
Constant x EXP_never	2.292	0.99	0.120	0.06	1.862	1.65	-2.153	-1.16
Constant x EXP_entry	1.299	0.59	-0.520	-0.26	1.227	0.98	0.312	0.16
Constant x EXP_exit	1.366	0.58	2.607	1.14	1.722	1.23	0.936	0.39
Constant x EXP_both	5.325	0.53	1.438	0.55	1.015	0.77	1.686	0.98
Industry dummies	yes		yes		yes		yes	
Region dummies	yes		yes		yes		yes	
Diagnostic statistics								
No. of Obs.	3229		979		15285		23841	
No. of groups	1051		337		4655		7932	
Hansen-test (χ^2)	91.40		129.89		359.54*		334.72	
AR(1) z-statistic	-1.30		-1.45		-6.18***		-6.19***	
AR(2) z-statistic	-1.97**		-1.09		-0.04		-0.25	

The long-run parameter estimates that refer to the impact of 'learning-by-exporting' for the IV, control function and matching models are shown in Table 4. There are 3 sets of estimates that consider whether post-entry exporting improves productivity: firstly, there are the terms that show whether firms new to exporting have the expected pattern of significant, positive estimates in t and $t+1$ (cf. the EXP_{entry} variables); second, we measure the TFP impacts for those firms leaving exporting expecting that (if learning-by-exporting is prevalent) there should be significant, negative effects in t and $t+1$ for firms that exit overseas markets (cf. the EXP_{exit} variables); lastly, we also allow for the effect on TFP of those that both enter and leave export markets, with the expectation of significant, positive estimates in t and $t+1$ (cf. the EXP_{both} variables).

The results show that generally all three approaches to controlling for selectivity effects produce broadly similar results. The sample selectivity terms (λ_0 and λ_1) are generally insignificant, suggesting that the IV model has adequately controlled for potential selectivity bias. The matching approach results in substantial reductions in the number of observations available in those industries where exporters are in the minority, and the loss of exporters without 'common support' in those sectors where the majority of firms do export,[31] but the parameter estimates obtained are generally not too different to those obtained using the standard IV approach.

[31] We use the 'pstest' procedure available in STATA 9 to inspect the extent of covariate balancing after matching (see Leuven and Sianesi, 2003, for details of this test). In all cases the matched exporter and non-exporter sub-groups have the same mean propensity scores, and there is always a 100% reduction in 'bias' with respect to the values of propensity scores in the matched sample.

Table 4: Long-run 'learning-by-exporting' effect for certain UK industries, 1996-2004

	AGF	FBT	TCL	WPP	CRR	MET	ENG	OMF
IV model (GMM)								
EXP_entry $_{t+1}$	0.061	-0.013	0.066	0.678*	0.242	-0.004	0.112	-0.094
EXP_entry $_{t}$	-0.012	0.117**	0.173	-0.228	0.030	-0.043	0.278***	0.272***
EXP_entry $_{t-1}$	-0.066	-0.019	-0.094	-0.238**	0.068	-0.052	-0.215**	-0.084*
EXP_exit $_{t+1}$	0.084	-0.126*	-0.284*	0.107	-0.186*	-0.264***	0.098	-0.068
EXP_exit $_{t}$	0.133	-0.054	-0.072	0.118	-0.692***	0.120	-0.091	0.094
EXP_exit $_{t-1}$	-0.447	-0.049	0.157	-0.236	0.399*	0.237***	-0.114*	0.055
EXP_both $_{t+1}$	0.689***	-0.021	-0.086	0.076	-0.025	-0.072	-0.048	-0.045
EXP_both $_{t}$	0.042	0.211**	-0.153	-0.013	-0.004	0.071	0.036	0.042
EXP_both $_{t-1}$	0.260	-0.104*	0.110	0.057	-0.017	-0.008	0.009	-0.055
No. of Obs.	1702	3065	2223	6903	4629	7075	9596	3731
No. of groups	508	741	530	1798	1107	1719	2252	948
Control function								
EXP_entry $_{t+1}$	0.074	-0.014	0.013	0.743**	0.256	-0.013	0.094	-0.102
EXP_entry $_{t}$	-0.061	0.271**	0.298	0.390	-0.041	0.039	0.410*	0.353
EXP_entry $_{t-1}$	-0.043	-0.013	-0.157	-0.329***	0.056	-0.065	-0.200*	-0.063
EXP_exit $_{t+1}$	0.086	-0.108*	-0.272	0.127	-0.181**	-0.198***	0.043	-0.068
EXP_exit $_{t}$	0.117	-0.257	-0.029	-0.433	-0.476	-0.001	-0.281	-0.066
EXP_exit $_{t-1}$	-0.383	-0.015	0.174	-0.272**	0.295	0.215***	-0.102*	0.070
EXP_both $_{t+1}$	0.693***	-0.054	-0.115	0.056	0.006	-0.053	-0.051	-0.051
EXP_both $_{t}$	0.018	0.369**	-0.117	0.463**	-0.065	0.118	0.222	0.092
EXP_both $_{t-1}$	0.283	-0.158*	0.103	0.035	0.001	-0.010	0.025	-0.045
λ_1	0.009	-0.014	0.009	-0.201***	0.109	-0.040	0.012	0.017
λ_0	0.058	-0.240***	-0.014	0.352	0.015	0.007	-0.122*	-0.121
No. of Obs.	1702	3065	2223	6903	4629	7075	9596	3731
No. of groups	508	741	530	1798	1107	1719	2252	948
Matched sample								
EXP_entry $_{t+1}$	0.048	0.020	-0.043	0.533**	0.241*	0.008	0.115	-0.063
EXP_entry $_{t}$	0.009	0.093**	0.340*	-0.113	-0.001	-0.065	0.276***	0.278***
EXP_entry $_{t-1}$	0.025	0.001	-0.031	-0.246***	0.082	-0.022	-0.201*	-0.136*
EXP_exit $_{t+1}$	0.036	-0.092*	-0.349*	0.097	-0.192*	-0.281***	0.092	-0.067
EXP_exit $_{t}$	-0.006	-0.077	0.039	0.120	-0.729***	0.176*	-0.075	0.108
EXP_exit $_{t-1}$	-0.415	-0.042	0.200	-0.254*	0.436*	0.212***	-0.106*	0.052
EXP_both $_{t+1}$	0.694	-0.040	-0.091	0.086	-0.006	-0.072	-0.039	-0.058
EXP_both $_{t}$	0.026	0.185**	-0.057	-0.002	0.001	0.070	0.035	0.038
EXP_both $_{t-1}$	0.309***	-0.063	0.205	0.064	-0.012	-0.010	-0.006	-0.088
No. of Obs.	682	2564	2100	5178	4525	6386	3731	3443
No. of groups	261	685	509	1526	1089	1610	948	890

Notes: Refer to Table 2 for details of industry group codes. The 2-step GMM system estimator in STATA 9 is used using *FAME* data in conjunction with weights; the instrument set includes lagged values of the RHS variables in the model as well as $ln\ Age_{it}$ and $Intang_{it}$. Standard errors are obtained using the 'delta' method. See Table 3 for details of estimation of other variables. $^{***/**/*}$ significant at the 1%/5%/10% level.

Table 4 (cont.)

	CON	RSM	WHO	RHR	TRA	POT	FIN	BUS
IV model								
EXP_entry $_{t+1}$	0.069	0.051	-0.341	-0.605**	0.122	-0.001	-0.314	-0.260
EXP_entry $_{t}$	0.101*	0.065	-0.376*	0.104	-0.025	0.135***	0.673***	0.649**
EXP_entry $_{t-1}$	-0.123	0.019	-0.157	-0.067	-0.095	0.047	0.106	-0.160
EXP_exit $_{t+1}$	0.069	-0.446***	-0.426*	-0.111	-0.247*	0.102**	-0.267	-0.049
EXP_exit $_{t}$	-0.151	0.048	0.000	-0.596	0.033	-0.736**	0.115	0.442
EXP_exit $_{t-1}$	-0.004	0.131*	-0.375*	0.111	0.087	0.359	-0.012	0.023
EXP_both $_{t+1}$	0.033	0.166	-0.213**	0.566	-0.277	0.247	0.235	-0.434
EXP_both $_{t}$	0.026	0.047	0.181	0.135	-0.291	0.109	0.542**	0.025
EXP_both $_{t-1}$	-0.010	0.078	-0.132**	0.323	-0.051	0.063	0.007	-0.284*
No. of Obs.	10531	6094	12753	10414	3229	979	15285	23841
No. of groups	3055	1644	3389	2978	1051	337	4655	7932
Control function								
EXP_entry $_{t+1}$	0.068	0.144*	-0.291	-0.742	0.129	-0.045	-0.682*	-0.037
EXP_entry $_{t}$	0.300*	-0.366	2.033***	1.253	-0.130	0.139*	1.841***	1.325**
EXP_entry $_{t-1}$	0.066	0.171**	-0.158	-0.062	-0.110	-0.155	0.025	-0.370
EXP_exit $_{t+1}$	0.090	-0.383**	-0.314	-0.063	-0.260*	0.104***	-0.226	-0.028
EXP_exit $_{t}$	-0.549	0.588	-2.351***	-1.794	0.319	-0.675**	-0.800	-0.243
EXP_exit $_{t-1}$	-0.012	0.145	-0.236	0.064	0.092	0.502	-0.032	0.092
EXP_both $_{t+1}$	0.019	0.135	-0.239**	0.784	-0.018	0.226	0.333	-0.441
EXP_both $_{t}$	0.424	-0.434	2.460***	1.530	-0.230	1.211	1.582***	0.578
EXP_both $_{t-1}$	0.007	0.061	-0.087	0.369	0.282	-0.154	-0.066	-0.378***
λ_1	-0.122	0.099*	-0.594***	-0.178	0.042	-0.333*	-0.183*	-0.164
λ_0	-1.646	-0.289	-1.150***	-3.512	-0.534	-0.555	-2.217***	0.314
No. of Obs.	10531	6094	12753	10414	3225	979	15285	23841
No. of groups	3055	1644	3389	2978	1050	337	4655	7932
Matched sample								
EXP_entry $_{t+1}$	0.085*	0.029	-0.342	-0.749**	0.101	-0.033	-0.228	-0.202
EXP_entry $_{t}$	0.085**	0.076	-0.348*	0.124	0.102	0.201**	0.350***	0.303***
EXP_entry $_{t-1}$	-0.102**	0.003	-0.146	-0.058	0.015	0.072	0.116	0.003
EXP_exit $_{t+1}$	0.016	-0.380***	-0.450*	-0.143	-0.195**	0.080***	-0.105	0.019
EXP_exit $_{t}$	-0.142	0.000	0.025	-0.730	0.086	-0.681***	-0.113	0.085
EXP_exit $_{t-1}$	-0.003	0.093	-0.340	0.107	0.056	0.446	0.019	-0.054
EXP_both $_{t+1}$	0.030	0.063	-0.204***	0.631	-0.386*	0.156	0.064	-0.166
EXP_both $_{t}$	0.027	-0.037	0.167	0.097	-0.087	0.141	0.430**	0.091
EXP_both $_{t-1}$	-0.011	-0.038	-0.132**	0.344	-0.010	0.105	0.029	-0.168*
No. of Obs.	2941	1326	10688	2669	1301	666	3992	16164
No. of groups	1338	659	3118	1170	623	266	1807	5911

Table 4 shows that ‘learning-by-exporting’ is present but it is by no means universal, and even within industry groups there are differences for entrants, exiting exporters, and those that experience both entry and exit into overseas markets. To summarise the results obtained, those parameter values that are significant (at the 15% level or better) are weighted by their shares in total (real) gross output to obtain an overall estimate for the UK economy (Table 5). Two sets of results are presented, with the second omitting the retail and wholesale sectors due to the generally atypical results these large sectors have. Overall, the second set of results in Table 5 show that there is a fairly substantial post-entry productivity effect for firms that are new to exporting (e.g. based on the IV model, a 34% long-run increase in TFP in the year of entry, and only a small effect of around 5% in the year following entry); firms exiting overseas markets overall experience negative productivity effects in the year they exit and subsequently (around 7-8% on average for the economy); while firms that enter and then exit experience large productivity gains whilst exporting (some 19% in the year of entry, but with a 5% decline the following year).

Our results differ in both approach and outcome to others for the UK. Besides weighting our data to ensure it is representative of the population of firms, and having a more extensive dataset (in terms of the number of observations and industries covered), we also use a dynamic GMM systems approach to directly estimating TFP within a production function model that attempts to control for both sample selection and endogeneity. Girma *et. al.* (2004) used unweighted matched data and a difference-in-differences approach[32], but TFP is obtained using a growth accounting model and thus there is no direct estimation of an *economic* model where causality can be consistently dealt with. Also constraining the underlying production function to exhibit constant returns-to-scale is likely to further bias any estimates of the exporting-productivity relationship, as the exporting variable(s) in the model have to

[32] Hence, their dependent variable is the *growth* of output ($\Delta ln\ Y_{it}$), or productivity, depending on the different specifications they use. Such a model cannot provide an estimate of the long-run impact of exporting on productivity levels, as long-run impacts by definition are omitted. This is not a trivial issue, as Equation (5) used here encompasses both short- and long-run impacts.

absorb some of the size effect – see van Biesebroeck (2005, section 5) for evidence on this. Nevertheless, Girma *et. al*. (*op. cit*.) found that the short-run impact of 'learning-by-exporting' on growth was important, although the impact was generally quite small.

Table 5: Average 'learning-by-exporting' effect, UK 1996-2004

	Weighted average all industries [a]	Weighted average all industries excl. Retail and Wholesale trade
IV model		
EXP_entry $_{t+1}$	-0.040	0.048
EXP_entry $_{t}$	0.191	0.343
EXP_entry $_{t-1}$	-0.025	-0.035
EXP_exit $_{t+1}$	-0.126	-0.085
EXP_exit $_{t}$	-0.053	-0.073
EXP_exit $_{t-1}$	-0.034	0.032
EXP_both $_{t+1}$	-0.066	-0.047
EXP_both $_{t}$	0.135	0.186
EXP_both $_{t-1}$	-0.047	0.048
Control function		
EXP_entry $_{t+1}$	-0.124	-0.171
EXP_entry $_{t}$	0.919	0.842
EXP_entry $_{t-1}$	-0.008	-0.011
EXP_exit $_{t+1}$	-0.103	-0.077
EXP_exit $_{t}$	-0.374	-0.023
EXP_exit $_{t-1}$	0.020	0.027
EXP_both $_{t+1}$	-0.062	-0.035
EXP_both $_{t}$	0.815	0.609
EXP_both $_{t-1}$	-0.037	-0.051
Matched sample		
EXP_entry $_{t+1}$	-0.057	0.050
EXP_entry $_{t}$	0.100	0.211
EXP_entry $_{t-1}$	-0.020	-0.027
EXP_exit $_{t+1}$	-0.124	-0.076
EXP_exit $_{t}$	-0.049	-0.068
EXP_exit $_{t-1}$	-0.036	0.022
EXP_both $_{t+1}$	-0.047	-0.021
EXP_both $_{t}$	0.133	0.149
EXP_both $_{t-1}$	-0.033	-0.018

[a] Average of all estimates in Table 4 that are significant at the 15% or better level (weighted by industry shares of total real gross output in all industries).

Our results are also consistent with those in Bernard and Jensen (2004); they found that in US manufacturing new entrants into export markets are rewarded with a surge in TFP especially during the first year post entry, and thereafter their productivity path becomes flatter, following that of continuous exporters (although with significantly lower productivity levels). In contrast, those that exit from exporting are characterised by a substantial deterioration in productivity to eventually resemble the flat growth trajectory of continuous non-exporters.

The aggregate results for the ‘control function’ model in Table 5 tend to be larger, after including the sample selectivity correction terms, while the results for the matched sample are generally lower than those obtained using the standard IV GMM model. Thus, there is some uncertainty as to the overall size of the ‘learning-by-exporting’ effect, although our results show that nonetheless this effect was present and important to UK firms during 1996-2004.

VI. Conclusions

This study provides an assessment of the extent to which productivity growth within firms may be stimulated by exporting. This involves measuring the impact on productivity of preparation for entering overseas markets (i.e. the self-selection hypothesis), as well as looking at productivity effects, which may occur following overseas market entry (i.e. ‘learning-by-exporting’ effect). In particular, we exploit the panel aspects of the data when undertaking appropriate econometric modelling, and also use techniques that ensure issues of endogeneity and sample selection are taken into account.

From estimating probit models determining which firms exported at any time during 1996-2004, using a weighted *FAME* dataset, our results for 16 separate UK industry groups (covering all the main marketed output sectors of the economy) confirm what most other similar studies have reported in the literature on self-selectivity. We find that firms with higher (labour) productivity in the previous year are significantly more likely to sell overseas in the current period. Also firms that are older or that possess intangible assets (e.g. R&D stock, brand recognition, goodwill, etc.) are generally much more likely to export.

In terms of the 'learning-by-exporting' effect associated with post-entry sales to overseas markets, we test the relationship between exporting and productivity using three approaches to controlling for selectivity effects: an IV model (with the age of the firm and whether it had intangible assets as the additional instruments used to control for selectivity); a control function approach (with the selectivity terms obtained from a first stage probability of exporting model included in the production function to control for bias); and a matching approach (based on the propensity scores obtained from the probability of exporting model). We have estimated production function models that incorporate the determinants of TFP, including exporting, and results show that generally all three approaches produce broadly similar results: 'learning-by-exporting' is present but by no means universal, and even within industry groups there are differences amongst entrants, exitors, and those that experience both entry and exit into overseas markets. However, in terms of the overall estimate for the UK economy, our findings suggest a fairly substantial post-entry productivity effect for firms new to exporting; a negative effect for firms exiting overseas markets in the year they quit and thereafter; and large productivity gains whilst exporting, of firms that both enter and exit.

In summary, this study differs in both approach and outcomes to others for the UK. Besides weighting the data to ensure its representativeness of the population of firms, and employing a more extensive dataset (in terms of the number of firms and industries covered), we also use a dynamic GMM systems approach to directly estimating TFP within a production function model that attempts to control for both sample selection and endogeneity. The main results obtained from the modelling of self-selectivity and 'learning-by-exporting' confirm that the productivity differential between exporters and non-exporters is attributable to a combination of pre-entry productivity increase (to overcome entry barriers) in all firms, and significant post-entry 'learning-by-exporting' effect in some UK industries during 1996-2004.

As to the policy implications arising from the above results, this study echoes the general conclusions reached by the DTI that since exporting leads to higher productivity, it is clearly beneficial for (more) firms to sell to overseas markets to obtain both the private and public benefits from doing so (DTI, 2006). Notably, our findings are in line with arguments that firms need an adequate knowledge-base, organisational capacities, and complementary assets/resources (especially intangible and human capital assets that lead to greater absorptive capacity) to overcome such entry barriers (Kogut and Zander, 1996). This leads us to conclude that the type and quality of firm specific assets are vital in breaking down export barriers; while the literature points to other factors that determine internationalisation (e.g. sector, networks, agglomerations, etc.), the results we have obtained confirm the key, central role of resources and capabilities, which is consistent of the international entrepreneurship literature particularly in the business/management area. From this we argue that policy should consider how it might best increase overseas market entry through ensuring that potential exporters have the requisite assets.

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Appendix

Table A1: Variable definitions used in the weighted *FAME* dataset

Variable	Definitions
Export	Dummy variable coded 1 if the firm has positive overseas turnover in any year during 1996-2004
EXP_always	Dummy variable coded 1 if the firm always exported throughout 1996-2004
EXP_never	Dummy variable coded 1 if the firm never exported throughout 1996-2004
EXP_entry[a]	Dummy variable coded 1 if the firm entered into exporting during 1996-2004
EXP_exit[a]	Dummy variable coded 1 if the firm exited exporting during 1996-2004
EXP_both[a]	Dummy variable coded 1 if the firm started and then stopped exporting more than once during 1996-2004
Gross output	Turnover (in £'000 2000 prices)
Intermediate inputs	Cost of sales minus remuneration (in £'000 2000 prices)
Capital stock	Tangible assets (in £'000 2000 prices)
Intangible assets	Non-monetary assets (e.g. innovation, goodwill, brand, etc.) coded 1 if > 0.
Labour productivity	Gross output per employee
Age	Age of the firm in years
Employment	Number of employees in the firm
Industry	3-digit industry (SIC2003)
Region	Standard Government Office regions based on postcodes information in *FAME*

[a] These variables also enter the model coded 1 in year *t* when the firm exports (otherwise coded 0 when it does not export in *t*). See the discussion following Equation (5).

Unpublished appendix

Table S1 (unpublished): Determinants of exporting by industries, UK 1996-2004 (cf. Equation 3)

Industries: / Independent variables:	AGF			FBT			TCL		
	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means
10-19 employees $_{(t-1)}$	-0.058	-2.58	0.178	-0.113	-3.45	0.207	0.192	6.01	0.152
20-49 employees $_{(t-1)}$	0.296	8.42	0.131	-0.100	-3.26	0.308	0.442	19.66	0.283
50-199 employees $_{(t-1)}$	0.316	9.35	0.172	0.138	3.92	0.223	0.503	25.22	0.273
200+ employees $_{(t-1)}$	0.557	12.93	0.073	0.280	6.57	0.121	0.419	28.08	0.108
ln labour productivity $_{(t-1)}$	0.030	3.89	4.030	0.137	11.76	4.043	0.214	14.82	3.969
Intangible assets $_{(t-1)}$ >0	-0.043	-1.95	0.126	0.142	5.02	0.220	0.109	2.94	0.103
ln age $_{(t-1)}$	0.076	7.74	2.921	0.008	0.68	2.801	0.062	5.16	2.912
North East	-0.160	-14.66	0.031	-0.153	-2.63	0.044	0.232	2.68	0.007
Yorkshire-Humberside	-0.101	-4.94	0.047	-0.041	-0.85	0.097	0.329	11.18	0.100
North West	-0.162	-14.68	0.048	0.115	1.98	0.060	0.114	2.26	0.146
West Midlands	-0.159	-14.36	0.046	0.570	15.16	0.090	0.222	5.25	0.112
East Midlands	-0.068	-3.63	0.132	0.149	2.61	0.066	0.330	10.65	0.144
South West	-0.166	-13.98	0.093	0.185	3.30	0.074	0.316	9.66	0.026
Eastern England	-0.159	-11.77	0.176	0.157	3.02	0.092	-0.011	-0.13	0.035
London	-0.101	-5.47	0.065	0.083	1.86	0.237	0.302	8.10	0.222
Scotland	-0.124	-8.55	0.087	0.118	2.40	0.113	0.159	3.23	0.132
Wales	-0.145	-12.25	0.022	-0.100	-1.68	0.038	0.297	8.27	0.021
Northern Ireland	–	–	–	0.487	1.82	0.001	-0.259	-1.42	0.003
No. of Obs.	2303			2522			2487		

Notes: Refer to Table 2 for details of industry group codes. $\partial\hat{p}/\partial x$ are marginal effects for each independent variable on the propensity to export (for binary variables, these are the effects of a discrete change from 0 to 1) and their corresponding *Z* statistics. Missing results for any region (e.g. Northern Ireland) is due to too few observations (leading to estimation problems); the South East region comprises the benchmark. SIC industry dummies were included but not reported in the table.

Table S1 (cont.)

Independent variables: \ Industries:	WPP			CRR			MET		
	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means
10-19 employees $_{(t-1)}$	-0.008	-0.52	0.211	-0.061	-2.76	0.121	0.110	6.40	0.232
20-49 employees $_{(t-1)}$	0.161	9.43	0.194	0.133	10.86	0.211	0.321	21.26	0.187
50-199 employees $_{(t-1)}$	0.276	16.36	0.230	0.251	19.69	0.347	0.481	38.81	0.261
200+ employees $_{(t-1)}$	0.511	21.52	0.061	0.250	26.72	0.179	0.480	47.57	0.053
ln labour productivity $_{(t-1)}$	0.114	16.80	4.212	0.025	3.49	4.363	0.160	17.57	4.040
Intangible assets $_{(t-1)}$ >0	0.087	5.45	0.144	0.100	7.12	0.175	0.280	16.38	0.120
ln age $_{(t-1)}$	0.044	8.71	2.609	0.024	3.98	2.853	0.047	6.27	2.927
North East	-0.112	-5.24	0.036	0.127	4.57	0.015	-0.164	-4.80	0.034
Yorkshire-Humberside	0.055	2.08	0.044	0.126	9.31	0.097	0.019	0.71	0.081
North West	0.059	2.49	0.061	0.092	5.76	0.152	-0.103	-4.06	0.085
West Midlands	0.065	2.15	0.038	0.027	1.30	0.093	0.096	4.50	0.180
East Midlands	-0.032	-1.52	0.055	0.091	5.05	0.068	-0.204	-8.20	0.078
South West	-0.003	-0.15	0.078	0.017	0.73	0.080	-0.207	-8.20	0.076
Eastern England	0.014	0.74	0.107	0.099	5.80	0.147	-0.169	-7.48	0.123
London	0.024	1.70	0.298	0.010	0.53	0.150	-0.121	-5.16	0.104
Scotland	-0.076	-3.52	0.043	0.058	1.99	0.030	0.083	2.54	0.043
Wales	-0.026	-0.90	0.028	0.117	6.54	0.033	-0.246	-8.24	0.041
Northern Ireland	-0.170	-3.07	0.002	0.157	8.66	0.008	-0.347	-4.86	0.003
No. of Obs.	8375			5551			8633		

Table S1 (cont.)

Industries: / Independent variables:	ENG			OMF			CON		
	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means
10-19 employees $_{(t-1)}$	0.091	9.03	0.138	0.267	11.36	0.194	0.064	7.45	0.163
20-49 employees $_{(t-1)}$	0.139	15.61	0.235	0.264	10.75	0.162	0.112	10.50	0.134
50-199 employees $_{(t-1)}$	0.312	37.35	0.328	0.437	22.40	0.285	0.159	13.56	0.140
200+ employees $_{(t-1)}$	0.260	47.15	0.119	0.511	29.45	0.080	0.322	12.22	0.033
ln labour productivity $_{(t-1)}$	0.062	10.92	4.278	0.117	12.48	4.039	0.013	6.16	4.318
Intangible assets $_{(t-1)}$ >0	0.086	8.66	0.179	0.145	5.97	0.146	0.084	6.69	0.051
ln age $_{(t-1)}$	0.053	11.04	2.745	0.150	15.05	2.671	-0.001	-0.62	2.508
North East	-0.213	-6.48	0.028	-0.092	-1.29	0.014	-0.012	-1.45	0.031
Yorkshire-Humberside	0.042	2.60	0.069	-0.054	-1.64	0.111	0.001	0.17	0.049
North West	0.007	0.47	0.083	0.030	0.88	0.094	-0.018	-3.24	0.068
West Midlands	0.099	8.61	0.136	0.048	1.41	0.107	-0.027	-5.88	0.095
East Midlands	0.053	3.60	0.076	0.213	6.42	0.088	-0.011	-1.77	0.071
South West	0.066	4.65	0.078	0.156	4.46	0.088	-0.031	-6.86	0.101
Eastern England	0.027	1.99	0.125	-0.051	-1.50	0.091	-0.046	-12.47	0.151
London	-0.030	-2.11	0.134	-0.192	-7.27	0.173	-0.035	-8.57	0.199
Scotland	-0.186	-7.51	0.052	-0.242	-6.06	0.030	-0.032	-6.87	0.050
Wales	0.082	2.59	0.015	-0.191	-4.84	0.050	-0.016	-1.86	0.030
Northern Ireland	-0.089	-0.73	0.002	–	–	–	0.085	1.69	0.002
No. of Obs.	11794			4395			13430		

Table S1 (cont.)

Industries: / Independent variables:	RSM			WHO			RHR		
	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means
10-19 employees $_{(t-1)}$	0.095	8.33	0.252	0.044	3.73	0.167	0.020	4.36	0.200
20-49 employees $_{(t-1)}$	0.158	10.76	0.200	0.158	14.22	0.204	0.028	4.55	0.159
50-199 employees $_{(t-1)}$	0.220	9.49	0.087	0.203	15.52	0.129	0.053	5.96	0.113
200+ employees $_{(t-1)}$	0.253	5.16	0.017	0.363	21.58	0.048	0.117	3.78	0.016
ln labour productivity $_{(t-1)}$	0.007	2.09	4.469	0.077	19.06	4.882	0.025	13.22	3.935
Intangible assets $_{(t-1)}$ >0	0.010	0.97	0.097	0.056	4.14	0.111	-0.014	-5.27	0.155
ln age $_{(t-1)}$	-0.002	-0.51	2.597	-0.010	-2.27	2.704	0.000	-0.10	2.485
North East	-0.060	-8.35	0.018	-0.207	-9.29	0.024	-0.017	-3.03	0.028
Yorkshire-Humberside	0.111	4.13	0.035	0.046	2.59	0.074	0.006	0.69	0.048
North West	-0.011	-0.96	0.106	0.000	-0.01	0.073	-0.017	-4.72	0.095
West Midlands	0.214	9.15	0.100	-0.096	-6.37	0.109	0.010	1.24	0.058
East Midlands	0.079	4.50	0.102	0.061	3.21	0.067	-0.002	-0.26	0.058
South West	-0.030	-3.38	0.131	-0.167	-10.33	0.066	0.013	1.66	0.067
Eastern England	0.022	1.71	0.121	-0.010	-0.67	0.109	0.010	1.55	0.098
London	0.051	3.35	0.117	0.034	2.69	0.254	0.044	7.04	0.322
Scotland	-0.050	-5.46	0.024	-0.124	-6.01	0.037	0.028	2.37	0.039
Wales	0.154	5.18	0.041	-0.162	-6.04	0.018	-0.012	-2.00	0.032
Northern Ireland	-0.044	-1.65	0.002	0.152	2.58	0.005	–	–	–
No. of Obs.	7416			15747			12906		

Table S1 (cont.)

Independent variables: \ Industries:	TRA			POT		
	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means
10-19 employees $_{(t-1)}$	0.037	3.02	0.178	0.059	1.92	0.143
20-49 employees $_{(t-1)}$	0.141	9.85	0.182	0.074	2.49	0.182
50-199 employees $_{(t-1)}$	0.168	10.54	0.167	0.173	3.44	0.100
200+ employees $_{(t-1)}$	0.264	9.29	0.055	0.156	2.02	0.033
ln labour productivity $_{(t-1)}$	0.043	11.88	4.301	0.029	3.81	3.558
Intangible assets $_{(t-1)}$ >0	-0.006	-0.50	0.098	0.025	0.99	0.145
ln age $_{(t-1)}$	0.025	5.82	2.647	0.024	1.93	2.078
North East	-0.086	-7.71	0.028	0.360	2.59	0.013
Yorkshire-Humberside	0.028	1.56	0.061	-0.034	-1.34	0.057
North West	-0.047	-3.95	0.076	0.027	0.48	0.021
West Midlands	-0.082	-7.98	0.058	-0.058	-2.58	0.022
East Midlands	-0.032	-2.03	0.046	-0.090	-6.53	0.098
South West	-0.016	-1.00	0.061	-0.072	-4.24	0.080
Eastern England	-0.006	-0.47	0.137	0.129	2.42	0.059
London	-0.013	-1.23	0.328	0.026	1.28	0.294
Scotland	-0.087	-9.41	0.048	-0.071	-4.36	0.012
Wales	-0.072	-4.49	0.020	–	–	–
Northern Ireland						
No. of Obs.	8162			1146		

Table S1 (cont.)

Independent variables: \ Industries:	FIN			BUS		
	$\partial\hat{p}/\partial x$	*z*-value	Means	$\partial\hat{p}/\partial x$	*z*-value	Means
10-19 employees $_{(t-1)}$	0.046	6.90	0.143	0.215	23.91	0.127
20-49 employees $_{(t-1)}$	0.108	11.80	0.109	0.319	34.04	0.115
50-199 employees $_{(t-1)}$	0.177	14.95	0.084	0.390	39.78	0.104
200+ employees $_{(t-1)}$	0.319	16.27	0.039	0.374	25.42	0.046
ln labour productivity $_{(t-1)}$	0.014	9.67	4.097	0.083	34.85	3.823
Intangible assets $_{(t-1)}$ >0	0.004	0.83	0.121	0.069	8.17	0.109
ln age $_{(t-1)}$	0.004	2.02	2.498	0.032	10.33	2.066
North East	-0.048	-7.78	0.013	0.031	1.72	0.024
Yorkshire-Humberside	-0.034	-7.08	0.051	-0.028	-2.28	0.040
North West	-0.027	-5.38	0.071	-0.005	-0.47	0.063
West Midlands	-0.039	-8.42	0.079	0.011	0.95	0.058
East Midlands	-0.020	-2.67	0.040	-0.046	-3.91	0.046
South West	-0.033	-6.41	0.058	-0.049	-4.64	0.057
Eastern England	-0.025	-4.91	0.089	-0.038	-4.56	0.120
London	0.018	3.81	0.375	0.023	3.32	0.335
Scotland	-0.028	-4.30	0.037	-0.066	-5.90	0.039
Wales	-0.029	-2.92	0.014	-0.037	-2.16	0.018
Northern Ireland	0.006	0.17	0.002	-0.064	-1.43	0.002
No. of Obs.	21081			32432		