Linking Productivity to Trade in the Structural Estimation of Production within UK Manufacturing Industries

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Abstract

We explicitly consider company trade orientation and analyse productivity dynamics within 4-digit manufacturing industries, using FAME data on UK companies, over the 1994-2003 period. We extend the algorithm in Olley and Pakes (1996) to allow for a trade bias, driven by high productivity types selecting to exporting (Melitz, 2003) and are able to obtain consistent and unbiased estimates of the parameters of the production function and productivity, respectively. We demonstrate that the link between trade orientation and productivity within industries can only be established when one allows for trade orientation within the estimation procedure. We also show that over the period of analysis, aggregate productivity is driven by market share reallocations, away from inefficient and towards efficient companies, rather than from improvements in company level productivity.

KEYWORDS: Simultaneity, selection (exit and trade) biases, productivity dynamics, UK manufacturing companies, within 4-digit industries.

JEL CLASSIFICATION: F14 and D24

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I. INTRODUCTION

The co-existence of exporting with non-exporting companies within 4-digit industries is a strong feature of our UK data. Bernard, Eaton, Jensen and Kortum (2003) outline the same fact for the US. The purpose of this paper is to estimate productivity in a way that allows for endogenous selection to exporting and document contributions to aggregate productivity. This is achieved by adapting an algorithm developed in Olley and Pakes (1996). We apply the modified algorithm to an unbalanced panel of the UK exporting and non-exporting manufacturing companies, with annual observations for the period 1994 -2003, and estimate productivity within 4-digit industries.

Our approach brings together two strands of literature on productivity and exporting. In the first strand, studies estimate company total factor productivity, in a first step, and in a second step they proceed to link productivity to exporting and contributions to aggregate productivity.[1] It is our view that testing for a relationship between exporting and the unobservable (productivity), ex-post, is admitting that there is information that should have been used in the structural model of the unobservable in the estimation of production. Indeed theory and empirical evidence on selection mechanisms guide us. Melitz (2003) employs sunk costs associated with exporting that lead to high productivity companies selecting to exporting. Hence, selection generates productivity differences between exporters and non-exporters. Indeed, a second strand of empirical literature confirms this. Roberts and Tybout (1997) for Colombia, Bernard and Jensen (2001) for the US, and Bernard and Wagner (2001) for Germany, estimate selection to exporting regressions and document that sunk export-market entry costs seem important enough to generate immense persistence in company export market participation. Our data also confirm this pattern of persistence in export market participation.

Given this evidence, as argued in Van Biesebroeck (2003), one should jointly estimate an export market participation equation when estimating the parameters of the production function.[2] By allowing for selection to trade in the unobservable, we are able to obtain consistent estimates of the coefficients on labour and capital, amongst other observables. An unbiased productivity index

[1] Bernard and Jensen (1999), Pavcnik (2002), Lopez-Cordova (2002), and Fernandes (2001), for example, apply Olley and Pakes (1996) to approximate productivity in the first step and correlate it with trade in a second step.

[2] Van Biesebroeck (2003) and De Loecker (2004) also consider adapting the algorithm developed in Olley and Pakes (1996) to allow for an additional, selection-to-exporting rule, however their approaches differ from ours in the way trade orientation information is incorporated into the non-parametric model of the unobservable. Another difference is in data used; their samples are from less developed and transition countries, respectively while we use data from a mature market economy. Applying the Olley and Pakes (1996) framework is more appropriate for mature industries.

for exporters and non-exporters can then be backed out as a residual. Thus, we make a contribution to the efficiency and trade debate, adding new reliable evidence from the UK, the fifth largest exporter in the world.[3]

Adapting the algorithm of Olley and Pakes (1996) to allow for a selection to trade, is shown to back out more reliable estimates of the unobservable productivity. As a counterfactual, we show that ignoring the trade orientation of companies in the structural algorithm of Olley and Pakes (1996) leads to measures of productivity that are hard to correlate with trade orientation ex-post. We show this using OLS, GLS and Olley and Pakes (1996) estimators of productivity that do not allow for the trade orientation of companies. Our Olley-Pakes estimates of productivity that allow for endogenous trade orientation show clear and persistence differences in the mean and variance of productivity over-time, by trade orientation. Furthermore, ex-post regressions reveal a robust correlation only between the estimated unobservable using our modified algorithm and exporting status. We are also able to demonstrate that recent improvements in aggregate productivity of the UK manufacturing are driven by reallocation of market shares towards efficient and away from inefficient companies rather than from improvements in productivity within companies.

The remainder of the paper is structured as follows. Section II provides a brief overview of data. Section III outlines our behavioural model and the 4–step estimation procedure used in this paper. Our regression results are reported in sections IV. In section V we undertake our analysis of aggregate productivity while in Section VI offer conclusions.

II. The FAME Data

According to Bureau van Dijk, FAME is the most comprehensive database of UK companies available. Data cover all companies filing at the Companies House in the UK and information comprises detailed financial statements, ownership structure, activity description, direct

[3] In summary, the literature on efficiency and exporting comprises several papers covering various countries: Aw and Hwang (1995) and Aw, Chen, and Roberts (2001) on Taiwan; Bernard and Jensen (1995; 1999) on the US; Clerides, Lach and Tybout (1998) on Colombia, Mexico and Morocco; Bernard and Wagner (1997) on Germany; Kraay (1999) on China; Castellini (2001) on Italy; Delgado, Farinas and Ruano (2002) on Spain; Pavcnic (2002) on Chile. On the UK the only existing study that we are aware of is by Girma, Greenaway and Kneller (2002) covering the period 1988-1999. The studies cover a range of time periods and use a variety of methodologies. Importantly, every single study finds that exporters have higher productivity than non-exporters, a relationship that goes beyond size. They also typically find that exporting companies are bigger, more capital intensive and pay higher wages. The literature does disagree on the self-selection versus learning hypothesis. Castellini (2001) reports some evidence suggesting that the productivity of exporting companies may increase with increases in export intensity. For Chinese companies, Kraay (1999) reports evidence of learning by exporting as well as Van Biesebroeck (2003) - for exporters in Africa. Interestingly, Girma, Greenaway and Kneller (2002) is the only study that supports the learning hypothesis for a developed market economy – the UK. The evidence in Delgado, Farinas and Ruano (2001) is inconclusive and Bernard and Jensen (1995, 1999), Bernard and Wagner (1997), Clerides, Lach and Tybout (1998) and Aw and Hwang (1995) explicitly test for, but fail to find, any evidence to support the learning by exporting hypothesis.

exports, various financial ratios and credit scores.[4] The dataset used in our analysis contains annual records on more than 80,000 manufacturing companies over the period 1994-2003. The coverage of the data compared to the aggregate statistics reported by the UK Office for National Statistics is as follows: sales 86%, employment 92%, and exports 100%. The manufacturing sectors are identified on the bases of the current 2003 UK SIC at the 4-digit level and range between 1513 and 3663. All nominal monetary variables are converted into real values by deflating with the appropriate 4-digit UK SIC industry deflators taken from the Office for National Statistics. We use PPI to deflate sales and cost of materials, and an asset price deflator for capital and fixed investment variables.[5]

Statistics reported in Table 1 are calculated from the FAME sample of manufacturing companies over the period 1994-2003, on the basis of company averages. We first look at the prevalence of exporting among UK manufacturing companies. At one extreme, companies could export the same share of their total output. At the other, a few giant companies would account for all exports. In fact, of the roughly 80,000 companies in the sample only 15.6 percent report export sales over the period of analysis.

Previous work has sought to link trade orientation with industry. It turns out that exporting producers are quite spread out across industries. Figure 1 plots the distribution of industry export intensity: each of the 215, 4-digit manufacturing industries represented in the sample is placed in one of the 10 bins according to the percentage of companies in the industry that export. In almost all the industries, the fraction of companies that export lies between 10 and 50 percent. Hence, knowing what industry a company belongs to would not answer with sufficient certainty whether it exports. This fact, similar to the findings of Bernard, Eaton, Jensen, and Kortum (2003) for the US manufacturing, suggests that industry has less to do with exporting than standard trade models might suggest.

Not only are companies heterogeneous in whether they export, they also differ substantially in various crude measures of productivity. Figure 2(a) plots the distribution across companies of value added per worker (segregating exporters from non-exporters) relative to the overall mean.

[4] FAME is a combination of high quality information from Jordans with easy to use software which has been developed by Bureau van Dijk Electronic Publishing (BvD). The financial breakdown of the companies in the different FAME modules is as follows: FAME A - Turnover > £1.5 million or Profits > £150,000 or Shareholder Funds > £1.5 million; FAME B - Turnover > £500,000 and < £1.5 million or Shareholder Funds > £500,000 and < £1,500,000 or Fixed Assets or Current Assets or Current Liabilities or Long Term Liabilities > £500,000; FAME C - Fixed Assets or Current Assets or Current Liabilities or Long Term Liabilities > £150,000 and < £500,000; recently formed companies and other companies where full financial information is not available are also included in this module.

[5] Katayama, Lu, and Tybout (2003), and related studies, argue that as production functions should be a mapping of data on inputs and outputs, studies using revenues and expenditure data as proxies would produce biased productivity measures. As in this study, most use industry level deflators for output, raw material and capital assets to get back the quantity data needed. It is clear that inputs and outputs can be priced differently for exporters and non-exporters within narrowly defined industries. We note, however, that allowing for endogenous trade orientation in the unobservable will control, to certain degree, for a persistent exchange rate adjusted pricing gap between exporters and non-exporters in their use of inputs and their outputs within 4-digit industries. Time dummies can control for movements in the real effective exchange rate over-time within exporting and non-exporting sub-samples.

Similarly, Figure 2(b) plots the distributions across exporting and non-exporting companies of value added per worker relative to the 4-digit industry mean. While differences across industries certainly appear in the data, what is surprising is how little industry explains about exporting and productivity. Hence, a satisfactory explanation of company level behaviour must go beyond the industry dimension. Therefore, we consequently pursue an explanation of these facts that bypasses industries and goes directly to sub-samples defined by trade orientation at the company level.

Table 1 also shows the importance of export markets for the companies that do export. Interestingly, the vast majority of exporters export less than 30 percent of what they produce. Less than 10 percent of the exporting companies export more than 70 percent of their production. Even for the minority of companies that do export, domestic sales dominate. An answer to these facts is documented in Table 1 - exporters are much larger. They are almost 4 times the size of non-exporting companies on average, even when export revenues are excluded from the calculation. While only 15.6 percent of manufacturing companies report that they consistently export, these companies account for almost 75 percent of the output of UK manufacturing.

Our mission is to estimate total factor productivity (TFP) in a consistent manner, to document the TFP gaps and to cast light on the nature of these gaps between exporters and non-exporters, within 4-digit industries. In addition we hope to understand movements in aggregate productivity. The strategy of our empirical analysis implies that we run regressions within 4-digit industries by sub-samples defined according to company export status. This leaves us with the 46 largest 4-digit industries, with sufficient number of observations to run regressions for exporting and non-exporting sub-samples. These 46 largest 4-digit industries account for almost 90 percent of the UK manufacturing sales in our data. In terms of the smallest estimated sample, where the Olley-Pakes 4-step algorithm is applied, there are 60,683 observations for 9,209 companies. The coverage of the data from this sample compared to the aggregate statistics is 61% for exports, and 63% for employment. The correlations between the aggregate statistics series and the estimated sample series are as follows: value added (used in the regressions as dependent variable) - 0.93, employment - 0.98, exports - 0.93.

In Table 2 we document descriptive statistics of regression variables. Exporting companies are older, bigger in terms of value added, employment and capital, and invest more.[6] The detailed definitions of regression variables are as follow: *Value added* is total sales adjusted for changes in inventories, minus material costs in thousands of pounds sterling. We assume that materials used are in a constant proportion of output. *Exports* are the reported value of direct exports, in thousands of pounds sterling, recorded annually. The problem of potential undercounting, due to the fact that

[6] It is worth noting that export status is persistent over time as only 16 percent of companies switch between exporting and non-exporting, or the other way round, in our sample during the period of analysis. We mark a company as an exporter if we observe in the data exporting by the company in any year within a 3-year moving window.

indirect exports are not included in this measure is discussed by Bernard and Jensen (1995). *Labour* is number of full-time equivalent number of employees recorded annually. *Age* is constructed by using year of incorporation as a starting point. *Capital* is measured as total fixed assets by book value, in thousands of pounds sterling, recorded annually. *Investment* is constructed from the annually observed (for each period, t) capital stock, K and depreciation, δ using the perpetual inventory method: $I_t=K_{t+1}-(1-\delta)K_t$.

III. THE BEHAVIOURAL MODEL AND ESTIMATION PROCEDURE

As outlined in previous sections, the aim of this paper is to generate dynamic company-level productivity estimates. A necessary condition for this analysis is the computation of consistent estimates of production function parameters. Since productivity is not directly observable in our data, the possibility that survival and selection to exporting as well as choice of factors of production should depend on productivity type leads to complications. Yet this situation also provides opportunities to identify the unobservable, when attempting to estimate the parameters of a production function. The first complication appears if productivity levels observed by managers determine input levels. Thus, we face the classic simultaneity problem analysed by Marshak and Andrews (1944).

The second complication arises out of the fact that companies survive and some of them select to exporting based on productivity type, amongst other factors. The problems associated with the exit of companies are discussed in Olley and Pakes (1996). If the decision of companies to export is related to their productivity level, then we have an endogenous selection process based on unobserved productivity. This would create selection-to-trade bias in the production function estimates and lead to inconsistency of production function parameters. Our purpose is to incorporate the impact of trade in the algorithm for estimating the parameters of the production function. We allow for simultaneity and selection effects non-parametrically (no imposed functional form or distributional assumptions) in our estimation procedure.[7]

Companies within different 4-digit industries are assumed to produce with Cobb-Douglas technology. The log-linear production function to be estimated is given by:

$$y_{ijt} = \beta_0 + \beta_a a_{ijt} + \beta_k k_{ijt} + \beta_l l_{ijt} + \omega_{ijt} + \eta_{ijt}. \tag{1}$$

[7] As we noted in footnote 5, in differentiated product industries it is clear that inputs and outputs can be priced differently for exporters and non-exporters within narrowly defined industries. A further implication of controlling for this type of selection in the unobservable is that it may control for a persistent exchange rate adjusted pricing gap between exporters and non-exporters in their use of inputs and outputs. Movements in the real effective exchange rate over time, within 4-digit industries, among other factors, are controlled for by using time dummies in exporting and non-exporting sub-samples

Thus, the log of company *i's* in industry *j* value added at time *t*, y_{ijt}, is modelled as a function of the logs of that company's state variables at *t*, namely age, a_{ijt}, capital, k_{ijt}, and the choice variable labour, l_{ijt}. The error structure is comprised of a stochastic component, η_{ijt}, with zero expected mean, and a component that represents unobserved productivity differences, ω_{ijt}. Both ω_{ijt} and η_{ijt} are unobserved, but ω_{ijt} is a state variable, and thus affects company's choice variables. On the other hand η_{ijt} has zero expected mean given current information, and hence does not affect decisions.

Simultaneity means that an OLS estimator would provide biased estimates for inputs if ω_{ijt} is correlated with input use. For labour, the readily adjustable input, this is likely to create an upward bias, assuming a positive correlation with ω_{ijt}. Selection to exporting or exit will depend on productivity type as well as the capital stock (sunk cost). The coefficient on capital is likely to be underestimated by OLS as higher capital stocks induce companies to survive at low productivity. On the other hand, selection to exporting should bias the capital coefficient upwards. A higher capital stock would be needed to meet higher sunk cost and select into exporting for a given productivity. Omitted productivity type will lead to a bias in the estimate of the capital coefficient, the direction of which is difficult to predict. Other factors, such as higher mark-ups in export markets, could lead to higher likelihood of selection, for any given sunk costs or productivity type. Hence, it will be important to control for additional factors in the selection-to-exporting equation. Similar arguments for the exit decision are outlined in Olley and Pakes (1996).

Besides the above biases, fundamental problem afflicting productivity measure is associated with the fact that companies' choices of products is made at more disaggregated level than the information for aggregate company operations available in the data. This unobservable product choice implies endogenous selection into product markets by companies on the basis of heterogeneous production techniques and asymmetric demand. Thus, productivity measure will capture true variation in company productivity as well as variation in fixed and variable costs, and mark-ups. In the absence of product-specific data, which is a typical problem for micro datasets available, consistent estimates of company productivity can be obtained by allowing the parameters of the production technology to vary across companies making different (types of) products. The identifying information that we use here to sort companies by product types is the companies' export status. As argued above, exporters differ from non-exporters by both the production techniques they employ and the demand characteristics they face. Furthermore, we estimate separate production functions for exporters and non-exporters within each 4-digit manufacturing industry.

Next we outline our *four-step estimation procedure*. We assume that investment sequences, i_{ijt}, chase performance, to certain degree, and are short-run decisions that are mainly determined by state variables such as the observable stock of physical assets, k_{ijt}, age of the company, a_{ijt}, and the unobservable productivity type of the company, ω_{ijt}. We assume as in Olley and Pakes (1996) that $i_{ijt} = i_{ijt}(\omega_{ijt}, a_{ijt}, k_{ijt})$ and that this function is invertible and differentiable such that $\omega_{ijt} = h_{ijt}(i_{ijt}, a_{ijt}, k_{ijt})$. Equation (1) can then be rewritten as:

$$(Step\ 1) \qquad y_{ijt} = \beta_l l_{ijt} + \varphi_{ijt}(i_{ijt}, a_{ijt}, k_{ijt}) + \eta_{ijt},$$

where $\varphi_{ijt}(\bullet) = \beta_0 + \beta_a a_{ijt} + \beta_k k_{ijt} + h_{ijt}(\bullet)$ and is proxied with a third-order polynomial in i_{ijt}, a_{ijt}, and k_{ijt}. We use series estimators to proxy for the unknown functions instead of kernel estimators. The use of series estimators in this first step has well known limiting properties but in later steps is less well defined. Therefore, we use bootstrapping methods to recover the correct standard errors. Moreover, the approximation of unknown functions with kernel estimators has proven to generate similar results. In the estimation of the return to labour in the production function above, the model of the unobservable can be extended to also control for the selection biases previously discussed. The probability, ρ_{ijt}, of being an exporter and the probability, ρ^*_{ijt}, of exit are modelled given the company's productivity type and other set of characteristics, X_{ijt} and X^*_{ijt}, respectively:

$$(Step\ 2) \qquad Pr\{Export = 1 | \omega_{ijt}, a_{ijt}, k_{ijt}, X_{it}\} = \rho_{ijt}(i_{ijt}, a_{ijt}, k_{ijt}, X_{it}),$$

$$(Step\ 3) \qquad Pr\{Exit = 1 | \omega_{ijt}, a_{ijt}, k_{ijt}, X^*_{it}\} = \rho^*_{ijt}(i_{ijt}, a_{ijt}, k_{ijt}, X^*_{it}).$$

To obtain unbiased estimates of β_l, a partially linear, semi-parametric regression model is employed allowing for simultaneity and both selection biases. We proxy for $\varphi_{ijt}(\bullet)$ with a third order polynomial in i_{ijt}, a_{ijt}, k_{ijt}, ρ_{ijt}, and ρ^*_{ijt}. The model is estimated on sub-samples of companies in exporting and non-exporting states within 4-digit industries to allow for the possibility that the elasticity with respect to labour may be different, and in addition the parameters of the third order polynomial in i_{ijt}, a_{ijt}, k_{ijt}, ρ_{ijt}, and ρ^*_{ijt} are allowed to be different for exporting and non-exporting companies. X_{ijt} and X^*_{ijt} include controls for company characteristics, such as size, ownership and time dummies to proxy for real effective exchange rate movements.

In *step 4*, to distinguish the effect of capital and age on the investment and selection decisions from that on output, we estimate β_a and β_k using a non-linear least squares estimator:

$$(\textit{Step 4}) \qquad y_{ijt+1} - \beta_l l_{ijt+1} = c + \beta_a a_{ijt+1} + \beta_k k_{ijt+1} + \sum_{m=o}^{3-n-q} \sum_{n=0}^{3-q} \sum_{q=0}^{3} \beta_{mnq} \hat{h}_{ijt}^{m} \hat{\rho}_{ijt}^{n} \hat{\rho}_{ijt}^{*q} + e_{ijt+1}.$$

We proxy the fourth term on the right-hand side of the equation with a third order polynomial in estimates of h_{ijt} (•), ρ_{ijt}, and ρ^{*}_{ijt} where the estimate of h_{ijt} (•) = φ_{ijt} (•) - β_0 - $\beta_a a_{ijt}$ - $\beta_k k_{ijt}$. We assume that ω_{ijt} follows a first-order Markov process and use one-period lag in the non-linear structure for ω_{ijt}. Again the model is estimated in sub-samples of companies in exporting and non-exporting states to allow for different *β's* in exporting and non-exporting samples. We also include time dummies in our regressions to control for changes in variables common across exporting (or non-exporting) companies within a 4-digit industry.

Thus, we estimate what we feel are the most consistent and reliable *β's* and use them to compute *TFP* with and without the regression error. This will allow us to make accurate inferences on the productivity differences between exporting and non-exporting companies as well as document their contributions to aggregate productivity. Having estimated the different *β's* for exporting and non-exporting sub-samples, within each 4-digit industry, we back out productivity for each company as:

$$TFP_{ijt} = y_{ijt} - \beta_l l_{ijt} - \beta_k k_{ijt}. \tag{2}$$

We also calculate a productivity measure purged of the regression error and show the importance of such error when we link productivity measures to trade orientation.

IV. Estimation Results

In Table 3 we report weighted averages, using value added as weight, of the estimated coefficients from the 4-digit industry regressions. In applying our modified Olley-Pakes algorithm, for example, we run separate regressions for each of the top 46, 4-digit industries, on exporting and non-exporting sub-samples or 92 regressions, in total. First, however, we estimate regressions where export status of a company is not considered. Then we split samples within industries treating export status as exogenous (randomly assigned). Finally, we allow the selection to exporting and the survival in the industry to be endogenous. In this context OLS, GLS within group estimator, Olley-Pakes 2-step (no selection rules) are contrasted with the Olley-Pakes 3 step (incorporating selection to trade) and Olley-Pakes 4 step (selection to trade and exit) estimators. The standard errors of all Olley-Pakes estimation routines are bootstrapped using 1,000 replications.

Comparing results from OLS, GLS, and Olley-Pakes 2, 3 and 4-step estimates for sub-samples of exporters (E) and non-exporters (NE), we see that the coefficient on labour gets progressively smaller as we control for simultaneity (2-step), simultaneity and selection to exporting bias (3-step) and simultaneity and selection to exporting and exit biases (4-step). The R^2 on explaining movements in value added progressively increases as we incorporate a richer model of the unobservable. Next, we focus on four sets of important results related to our productivity estimates.

Results I: Presence of mean productivity gap between exporters and non-exporters

We compute productivity measures aggregating over exporting and non-exporting samples and over 4-digit industries where productivity at the company level, TFP_{ijt}, as specified in equation (2) contains the regression error by company. If we take away the regression errors we are left with the pure deterministic part of *TFP*, i.e., ω. In table 3, we report weighted averages, using value added as weight, of log company level productivity, ω, net of regression errors, utilising OLS, GLS, and Olley-Pakes 2, 3 and 4-step estimates for sub-samples of exporters (E) and non-exporters (NE). The (weighted) mean productivity gap between exporters and non-exporters is largest for estimates of productivity backed out from the parameters of the production functions estimated by either Olley-Pakes 3 or 4-step, when we allow for trade orientation bias.

Results II: Presence of differences in the variance of productivity between exporters and non-exporters

In Figures 3(a) the distribution of our estimates of productivity across exporting and non-exporting companies are compared, by graphing the log productivity distributions computed from OLS, GLS and 2-step Olley-Pakes estimates. Productivity measure is represented as a deviation from the 4-digit industry mean, with and without regression errors. In Figure 3(b) we repeat the same exercise by comparing productivity of exporters and non-exporters as a deviation from the 4-digit industry mean computed from OLS, GLS, and Olley-Pakes 2-step coefficient estimates where regressions are run on sub-samples defined by trade orientation within 4-digit industries. The productivity distributions again are graphed with and without regression errors. Finally, in Figure 3(c) we compare productivity of exporters and non-exporters, as deviations from the 4-digit industry mean, computed from Olley-Pakes 3 and 4-step coefficient estimates, with and without the regression error. Clearly, allowing the coefficients to vary across trade orientation types of companies within 4-digit industries makes a difference to the productivity estimates. Allowing for simultaneity bias gives us a richer deterministic model of the unobservable and a greater variance in the spread of productivity across exporters and non-exporters (last column and row of Figure 3(b)).

Finally, allowing for simultaneity and selection to exporting and exit biases gives us an even richer deterministic model of the unobservable and greater variance in the spread of productivity across exporters and non-exporters (last column and row of Figure 3(c)).

Results III: Persistence of differences in the productivity distributions of exporters and non-exporters

Next, we summarize the Olley-Pakes 4-step productivity distributions with kernel density estimates. In Figure 4(a), separate densities are drawn for exporters and non-exporters, for five annual cross-sections, with an interval of two years (1994, 1996, 1998, 2000, 2002). There is no substantial rightward shift in the productivity distributions over time. Furthermore, the comparison of kernel density distributions of exporters and non-exporters, in Figure 4(b), at the beginning and at the end of the period of analysis, 1994 and 2002, shows that there are important productivity differences between the two types and that these differences persist. The exporters' distribution clearly stochastically dominates the productivity distribution of non-exporters. This stochastic dominance of exporting companies is observed in 1994 and persists throughout the ten-year period. These distributions are ranked using the concept of stochastic dominance, and their differences are formally tested using Kolmogorov–Smirnov one and two-sided tests, which are significant at the 1-percent level.

Results IV: Ignoring trade orientation in the estimation of productivity leads to spurious correlations between productivity and exporting

We wish to show that omitting the control for selection to trade in the structural algorithm of Olley and Pakes (1996) leads to spurious measures of productivity that are misleading to correlate with trade orientation *ex-post*. We highlight this point in Tables 4(a) and 4(b) by comparing our 4-step Olley-Pakes estimates of the unobservable, *TFP*, (with and without the regression residuals) to naïve OLS, GLS and 2-step Olley-Pakes estimates that use no trade information (coefficient estimates reported in the first three columns of table 3). In Table 4(a) we see that company productivity is correlated with export status for all estimates of productivity once we include the regression error into our construction of *TFP* (results are weighted averages over regressions from the top 46, 4-digit industries).

In Table 4(b) we net out the regression error from the estimate of *TFP* and include this regression error as an explanatory variable. The correlation of the pure ω with exporting only survives when we have a rich deterministic model of productivity that allows for endogenous trade orientation. This demonstrates that the inferences made using OLS, GLS and Olley-Pakes estimators not allowing for trade orientation in the estimation of algorithm are not robust to the inclusion of first-step errors.

V. AGGREGATE PRODUCTIVITY

In the UK manufacturing there is a strong positive correlation (correlation coefficient of 0.75) between export intensity and aggregate productivity over the period of analysis as illustrated in Figure 5. This may lead one to think that recent improvements in TFP are export lead and industrial policy should encourage non-exporters switching to exporting. Indeed the idea that export growth causes aggregate productivity growth through various externalities is well founded (Beckerman, 1965; Kaldor, 1970). Yet, micro-data studies such as Disney, Haskel, and Heden (2003) and Barnes and Haskel (2000; 2001) indicate that the expansion of more efficient companies accounted for between one third and a half of the labour productivity growth in the UK during the 1990's and even for a larger share of TFP growth. In this section we confirm that market share expansion in efficient (exporting) companies drives aggregate productivity, rather than productivity improvements within companies. We see that such aggregate outcomes are pushed by mechanisms outlined in the Melitz (2003) model, driven by micro selection and market reallocation effects. One would be wrong to assume TFP is export lead.

To relate industry-level productivity to trade orientation, we start by defining industry productivity, P_t, as market-share weighted sum of the company productivity levels:

$$P_t = \sum_i s_{it}\omega_{it} \ , \tag{3}$$

where ω_{it} is company productivity as defined in previous sections and s_{it} is the value of company i's real sales relative to total industry sales in year t. With this formulation, shifts of output from low productivity to high productivity companies will contribute positively to industry productivity growth, even if no individual company experiences a productivity increase. This is appropriate because our ultimate interest is in the ability of the companies in the industry to convert the set of inputs used in the industry into output, and movements of resources from low to high productivity companies can be just as effective in increasing industry output as are productivity improvements in individual companies. As shown by Olley and Pakes (1996), equation 3 can be rewritten as:

$$P_t = \bar{P} + \sum_i \Delta s_{it}\Delta\omega_{it} \ , \tag{4}$$

where $\overline{P}$ is the un-weighted mean productivity over all companies in a particular industry, in year *t* and the Δ is used to represent a deviation from the un-weighted mean in year *t*. The second term in equation 4 is the sample covariance between company productivity and market share in year *t*, and summed up over the number of companies in the year. The larger this covariance, the higher the share of output that is allocated to more productive companies and the larger is industry productivity.

Table 5 reports the aggregate productivity level for each of the eleven aggregate industries in five cross-section years (1994, 1996, 1998, 2000, 2002). In addition, the decomposition according to equation 4 is reported as the covariance term is calculated separately for exporters and non-exporters, in the last two columns, respectively. The un-weighted mean level of productivity increases only modestly over time for every industry (group), except food and beverages (SIC 15) and basic and fabricated metals (SIC 27, 28) for which a modest decline is observed. The increase over the decade is largest for the electrical machinery (SIC 30, 31, 32) – 15%. Furthermore, in every industry, there is a positive covariance between company productivity and market share as this pattern is observed for most of the years, the exceptions being precision instruments (SIC 33) and to a lesser extend the electrical machinery (SIC 30, 31, 32) industries. Another important result to point out is that the covariance term is in general larger, often substantially, for exporters.

The observed general pattern indicates that a larger share of industry output is being concentrated in the more productive companies, and thus, industry productivity is higher than the un-weighted company mean. Unlike the un-weighted mean productivity, the covariance term magnitude does vary greatly over time and more so for exporters. This variation in the magnitude of the covariance terms indicates that shifts in market share reallocations rather than the company productivity distribution are the main source of aggregate industry productivity growth observed in Figure 5.

VI. CONCLUSION

We outline a methodology for estimating the parameters of a production function while linking the unobservable productivity to an endogenous company level trade orientation choice, amongst other factors. Our approach is theoretically motivated in Melitz (2003) and empirically supported by a literature pioneered by Roberts and Tybout (1997). We build the theoretical idea into a structural model of the unobservable and adapt the algorithm developed in Olley and Pakes (1996) to estimate the parameters of production functions for exporting and non-exporting sub-samples of companies within the UK 4-digit manufacturing industries, for the period 1994 -2003. Allowing for trade-orientation bias greatly enhances our ability to have consistent and unbiased estimates of the parameters of the production function. This allows us to demonstrate a clear-cut link between trade orientation and productivity, in terms of the mean, the variance and persistency in productivity. As a result, we show that recent improvements in aggregate productivity of the UK manufacturing are driven by productive companies getting bigger rather than from improvements in productivity within companies. These findings support Ricardian-type thinking in the modelling of trade as in Helpman and Krugman (1985), Helpman, Melitz, and Yeaple (2004) amongst others.

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Figure 1: Industry exporting intensity

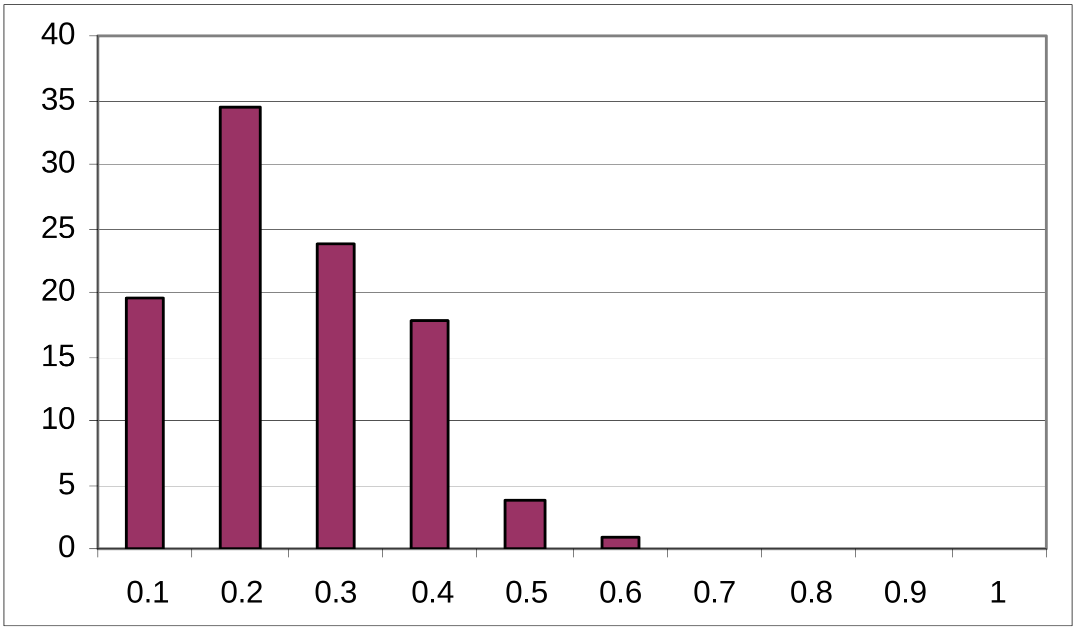


Figure 2(a): Distribution of company labour productivity (deviation from overall manufacturing mean)

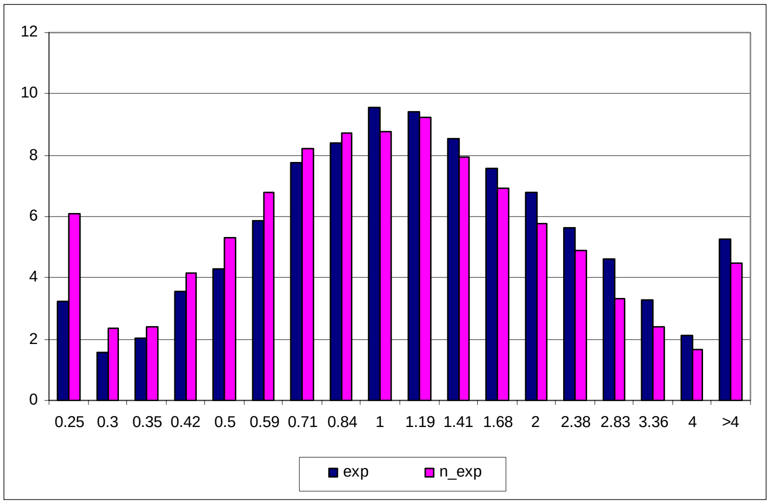


Figure 2(b): Distribution of company labour productivity (deviation from 4-digit industry mean)

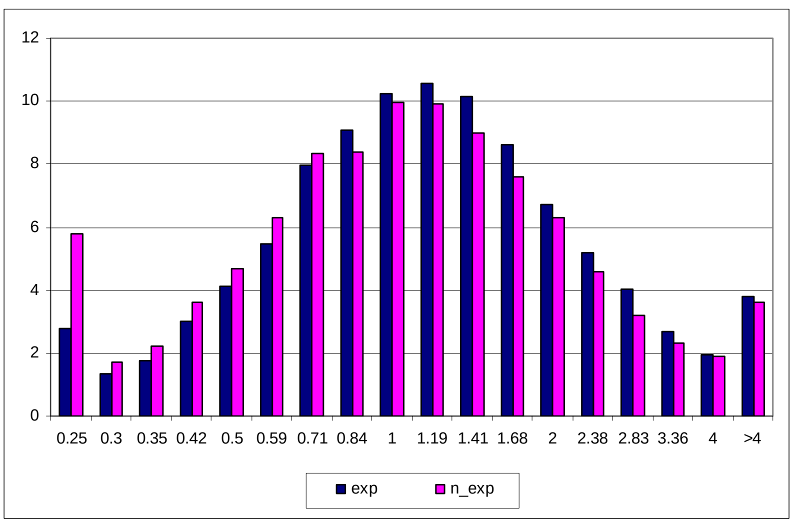
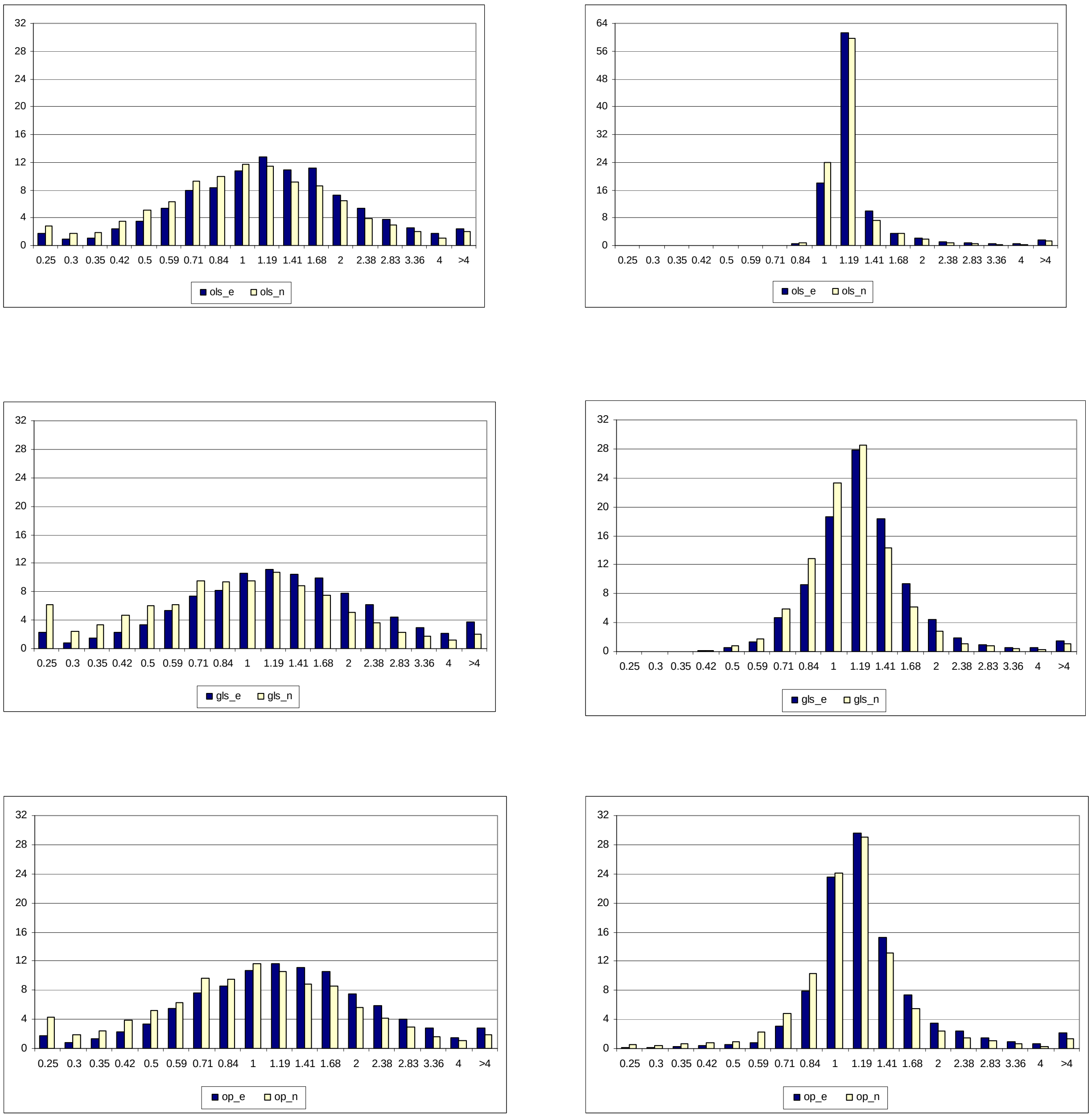


Figure 3(a): Comparing productivity distributions of exporters and non-exporters

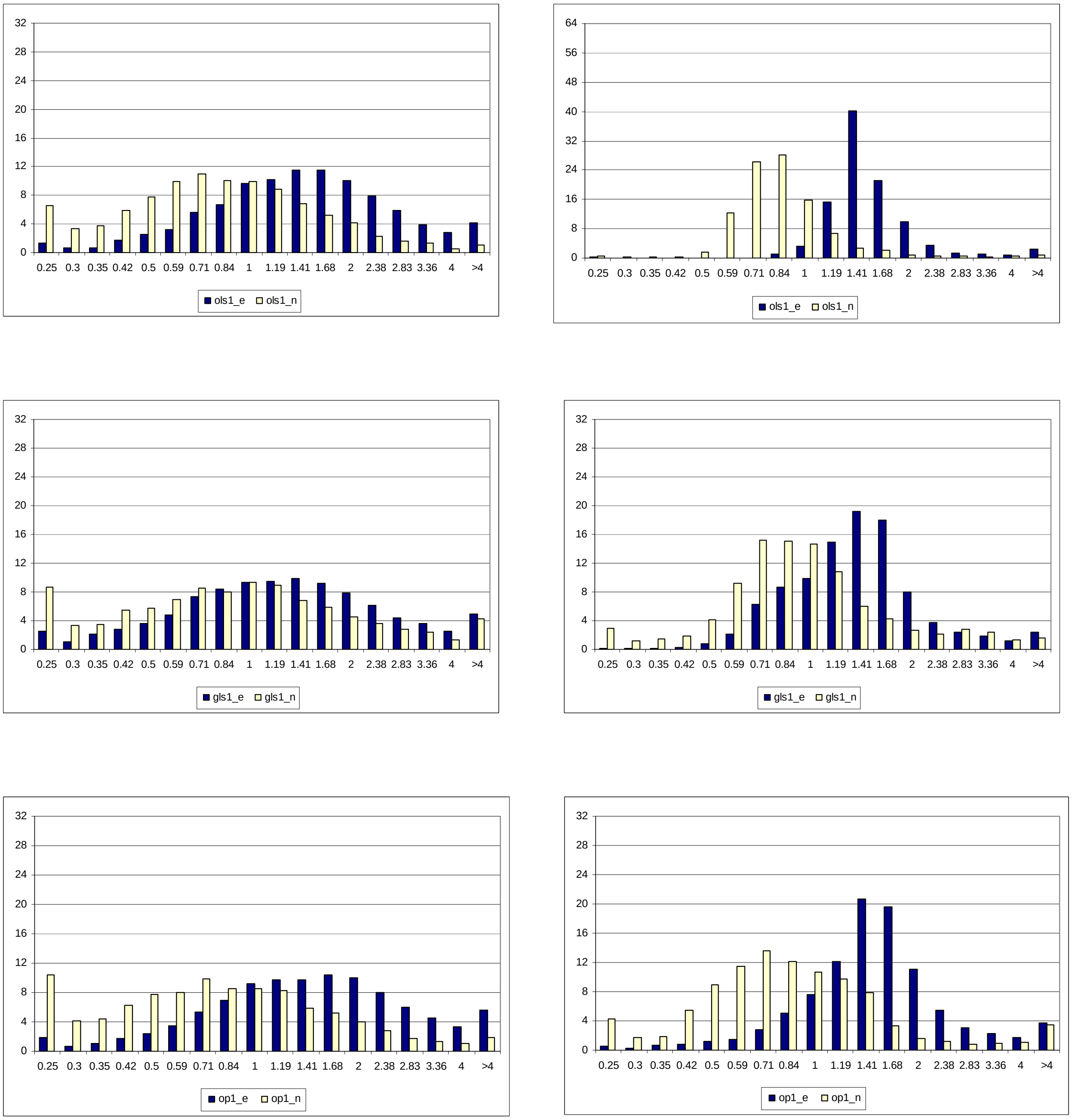
Productivity measure (deviation form 4-digit industry mean) calculated using OLS, GLS_fe, and Olley-Pakes 2-step coefficient estimates, with and without the first-stage errors



Note: Charts in the second column show the productivity measure calculated net of the regression error.

Figure 3(b): Comparing productivity distributions of exporters and non-exporters

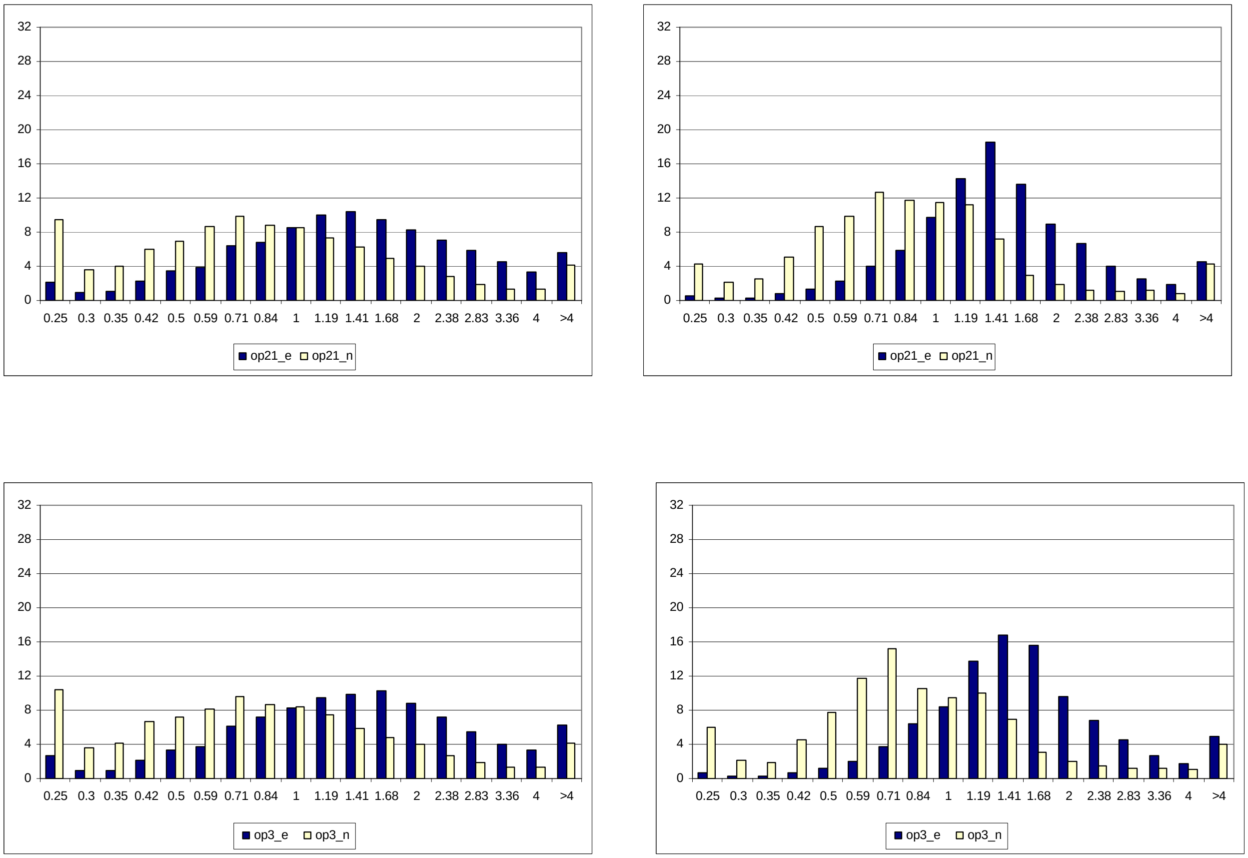
Productivity measure (deviation form 4-digit industry mean) calculated using OLS, GLS_fe, and Olley-Pakes 2-step coefficient estimates, splitting the sample into exporters and non-exporters, with and without the regression error



Note: Charts in the second column show the productivity measure calculated net of the regression error.

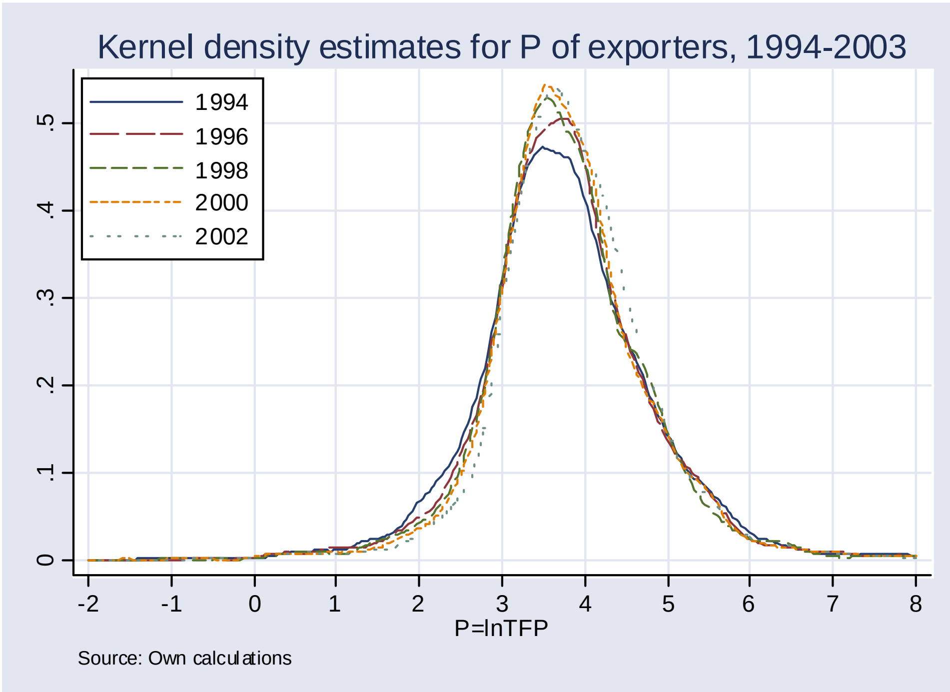
Figure 3(c): Comparing productivity distributions of exporters and non-exporters

Productivity measure (deviation form 4-digit industry mean) calculated using Olley-Pakes 3-step and Olley-Pakes 4-step coefficient estimates, with and without the regression error



Note: Charts in the second column show the productivity measure calculated net of the regression error.

Figure 4(a): Distribution comparisons using Olley-Pakes 4-step estimates of productivity



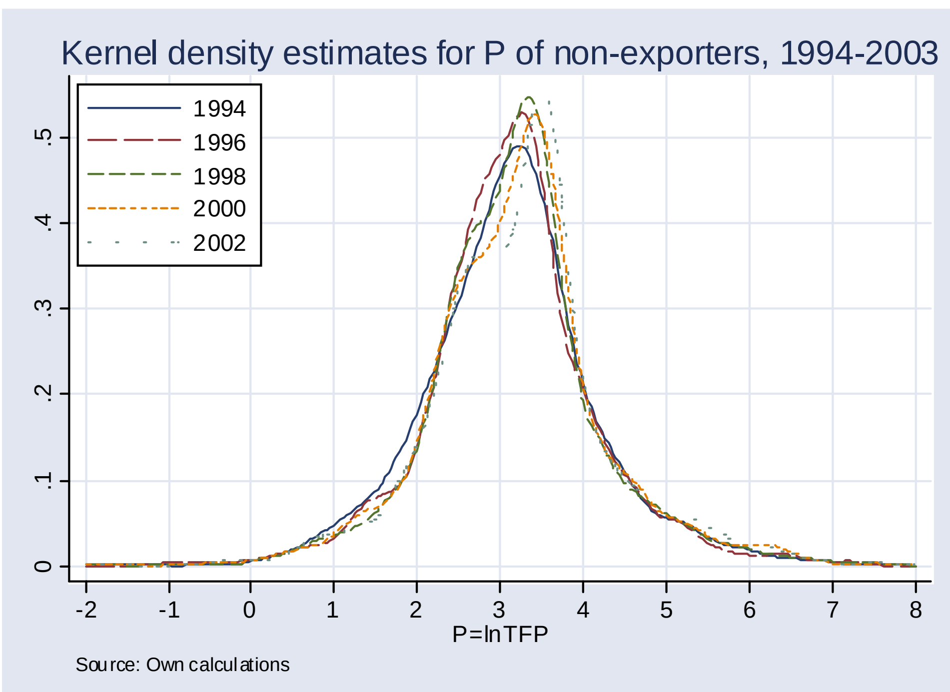
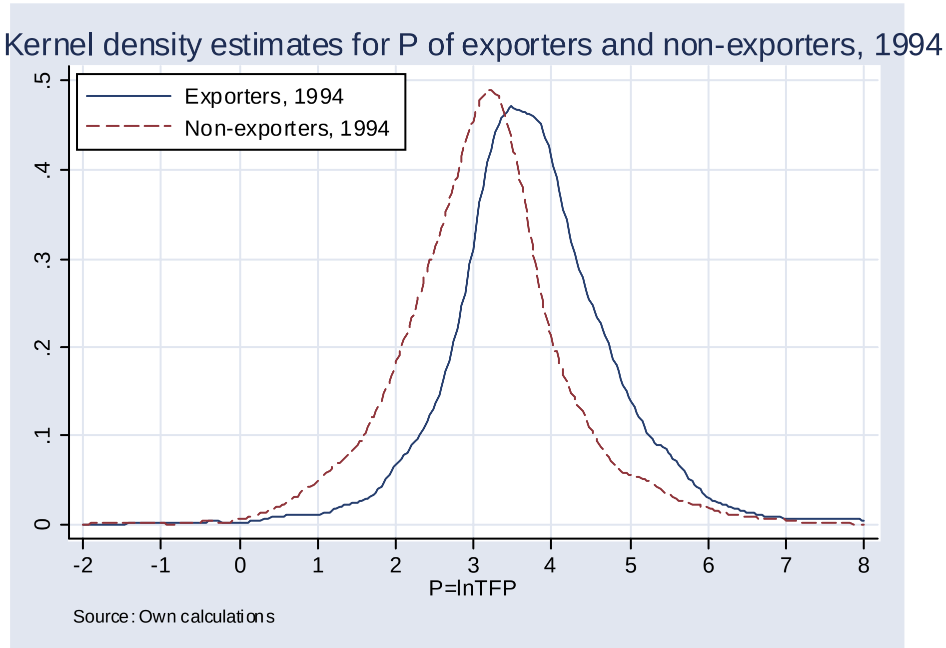


Figure 4(b): Distribution comparisons using Olley-Pakes 4-step estimates of productivity



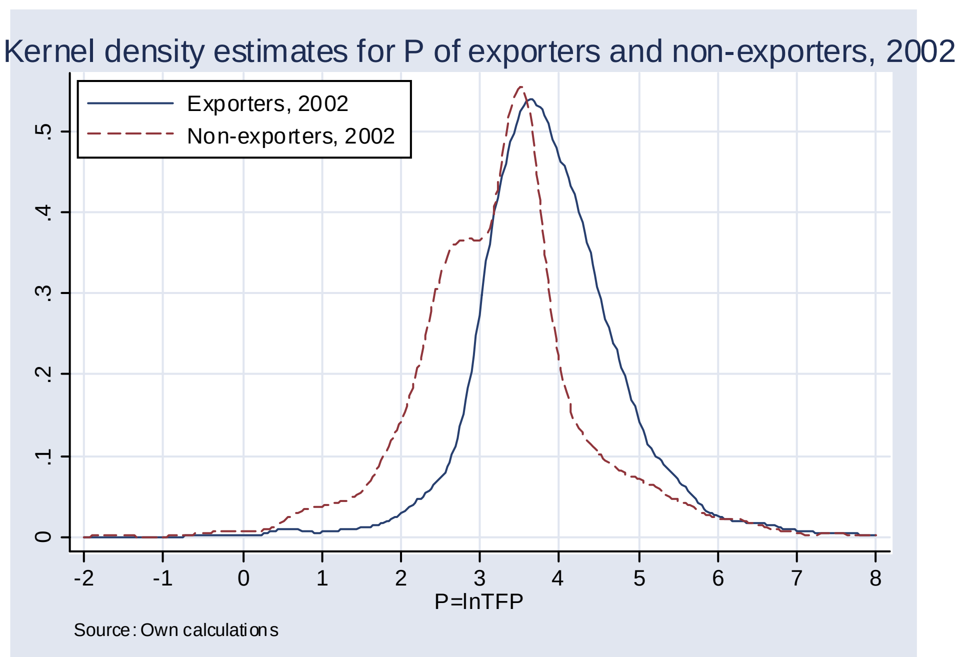
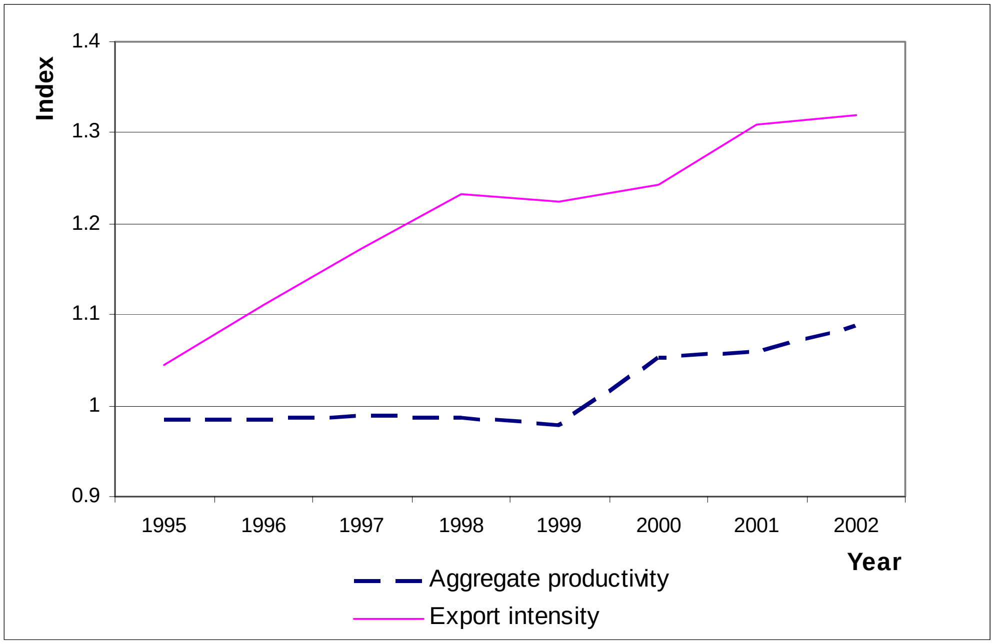


Figure 5: Aggregate productivity of the UK manufacturing and export intensity (exports/value added), 1994-2003



Note: Indexes are normalised at 1 for 1994.

Table 1: Company level facts on exporting

Exporter share	Percentage of all companies	Percentage of total output
	15.6	74.4
Productivity	**Standard deviation of log productivity (%)**	**Exporter less non-exporter average log productivity (%)**
Labour productivity (LP)	90.2	16.8
Labour productivity (LP) (*Within Industries*)	85.2	13.3
Exporter size advantage	**Ratio of average UK sales**	**Ratio of average total sales**
	3.8	6.5
Export intensity (%)	**Percentage of all exporters**	**Percentage of total output of exporters**
0 to 30	66.7	41.7
30 to 70	25.8	32.4
70 to 100	7.5	25.8

Note: The statistics are calculated from average company characteristics over the 1994-2003 period. Labour productivity (LP) is measured as value added per worker. Heterogeneity is the standard deviation of the logarithm of LP, multiplied by 100. The productivity advantage of exporters is the difference (multiplied by 100) in the mean logarithms of productivity between exporting and non-exporting companies. Within industry indicates that we subtract (from the log of productivity for each company) average log productivity of the appropriate 4-digit industry. The size advantage of exporters is the average shipments of exporting companies relative to the average for non-exporting companies, presented as a simple ratio.

Table 2: Summary Statistics

Variables	Age			Value added			Tangible fixed assets			Employment			Investment		
	E	N	T	E	N	T	E	N	T	E	N	T	E	N	T
1994	26.1	21.9	24.4	18.3	5.6	13.4	20.4	6.0	14.8	535	196	403	-	-	-
	(24.0)	(20.6)	(22.8)	(180)	(48)	(144)	(349)	(54)	(275)	(2807)	(1559)	(2404)			
1995	25.7	20.5	23.5	19.0	5.2	13.3	20.4	5.3	14.1	540	172	387	4.0	1.2	2.9
	(23.6)	(20.0)	22.3)	(201)	(47)	(157)	(328)	(51)	(254)	(2942)	(1297)	(2407)	(49)	(10)	(39)
1996	25.5	20.4	23.3	18.5	5.2	12.9	19.2	5.1	13.2	531	170	378	3.5	1.0	2.5
	(23.5)	(19.7)	(22.1)	(206)	(47)	(159)	(304)	(50)	(232)	(2948)	(1273)	(2391)	(52)	(7)	(40)
1997	25.7	20.8	23.7	18.4	5.8	13.2	19.7	5.5	13.8	519	180	378	4.3	1.3	3.1
	(23.6)	(19.9)	(22.3)	(211)	(46)	(164)	(313)	(46)	241)	(2890)	(1190)	(2344)	(59)	(11)	(46)
1998	25.7	20.6	23.6	18.6	6.1	13.4	22.9	5.8	15.9	516	189	382	8.5	1.6	5.8
	(23.7)	(20.1)	(22.4)	(220)	(41)	(171)	(500)	(45)	(385)	(3321)	(1066)	(2643)	(292)	(12)	(227)
1999	25.7	20.1	23.4	20.2	6.0	14.4	22.8	5.9	15.8	503	187	373	4.8	1.8	3.6
	(23.7)	(20.0)	(22.4)	(255)	(40)	(198)	(495)	(41)	(381)	(3175)	(985)	(2522)	(82)	(19)	(64)
2000	25.7	20.0	23.4	20.8	11.3	17.0	27.4	8.1	19.6	512	217	392	7.9	1.6	5.4
	(23.6)	(19.7)	(22.3)	(284)	(254)	(273)	(752)	(125)	(585)	(3189)	(2125)	(2809)	(333)	(26)	(260)
2001	26.2	20.3	23.8	22.0	12.5	18.1	28.1	8.9	20.3	532	237	412	4.5	1.9	3.5
	(23.5)	(20.0)	(22.4)	(323)	(280)	(306)	(781)	(130)	(607)	(3458)	(2217)	(3020)	(115)	(26)	(91)
2002	26.7	20.6	24.2	25.1	15.5	21.1	29.2	11.7	22.1	513	282	418	4.6	2.0	3.6
	(23.6)	(20.4)	(22.5)	(315)	(309)	(313)	(822)	(146)	(638)	(3256)	(2443)	(2946)	(130)	(25)	(101)
2003	28.0	20.6	25.0	40.6	23.0	33.4	41.9	15.6	31.3	668	319	526	5.0	2.2	3.9
	(24.1)	(19.7)	(22.7)	(479)	(433)	(461)	(1042)	(194)	(812)	(4163)	(3136)	(3782)	(85)	(22)	(67)
Average	26.0	20.6	23.8	21.3	9.0	16.3	24.5	7.4	17.5	530	210	399	5.3	1.6	3.8
	(23.7)	(20.0)	(22.4)	(269)	(193)	(241)	(599)	(96)	(464)	(3193)	(1772)	(2706)	(173)	(19)	(135)

Note: Number of observations is 41,935 for exporters (E), 29,177 for non-exporters (N), and 71,112 for the total sample (T) over the 1994-2003 period. Monetary values are in millions of constant (with respect to year 2000) British pounds. Standard deviations are in parentheses. * Export sales are averaged over the exporter sub-sample.

Table 3: Weighted average coefficient estimates for the total sample of UK manufacturing companies, 1994-2003

Parameters	Estimation method												
	Export status not considered			Export status considered									
				Exogenous						Endogenous			
	OLS	GLS_fe	Olley-Pakes 2-step	OLS		GLS_fe		Olley-Pakes 2-step		Olley-Pakes 3-step		Olley-Pakes 4-step	
				E	NE	E	NE	E	NE	E	NE	E	NE
b_l	**0.75**	**0.65**	**0.55**	**0.74**	**0.75**	**0.68**	**0.63**	**0.58**	**0.49**	**0.58**	**0.47**	**0.52**	**0.41**
s.e	0.02	0.04	0.02	0.03	0.03	0.04	0.05	0.03	0.03	0.03	0.04	0.03	0.04
b_k	**0.17**	**0.09**	**0.12**	**0.13**	**0.20**	**0.07**	**0.12**	**0.12**	**0.12**	**0.11**	**0.12**	**0.10**	**0.11**
s.e.	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.02	0.03	0.02	0.02	0.02
b_a	**0.02**	**0.24**	**0.02**	**0.02**	**-0.01**	**0.20**	**0.30**	**0.08**	**-0.02**	**0.05**	**-0.03**	**0.01**	**0.03**
s.e	0.02	0.06	0.08	0.02	0.03	0.08	0.08	0.11	0.09	0.07	0.05	0.05	0.04
log ω	**3.16**	**4.20**	**3.86**	**3.52**	**2.90**	**4.45**	**3.92**	**4.16**	**3.40**	**4.59**	**3.81**	**4.44**	**3.75**
s.d.	0.63	0.90	0.98	0.69	0.61	0.94	1.08	1.01	1.07	1.04	1.03	1.05	1.15
R^2	0.77	0.73	0.97	0.72	0.77	0.69	0.71	0.97	0.97	0.98	0.98	0.98	0.98
No obs.	71,112	71,112	66,452	41,935	29,177	41,935	29,177	40,441	26,011	40,105	25,899	36,772	23,911

Note: Coefficient estimates reported here are weighted averages of coefficients estimated within each 4-digit industry in the sample.

Table 4(a): Determinants of company productivity

OLS models of productivity level determinants (s.e. in parentheses)		
	OLS estimates of productivity measure (with regression error)	
EXPORTER	**0.118** (0.036)	**0.138** (0.037)
Age		-0.008 (0.018)
Capital		-0.015 (0.008)
Time trend		Yes
	GLS estimates of productivity measure (with regression error)	
EXPORTER	**0.299** (0.040)	**0.174** (0.039)
Age		0.005 (0.019)
Capital		**0.103** (0.008)
Time trend		Yes
	Olley-Pakes 2-step estimates of productivity measure (with regression error)	
EXPORTER	**0.182** (0.037)	**0.147** (0.038)
Age		-0.003 (0.019)
Capital		**0.027** (0.008)
Time trend		Yes
	Olley-Pakes 4-step estimates of productivity measure (with regression error)	
EXPORTER	**0.575** (0.041)	**0.528** (0.042)
Age		-0.005 (0.020)
Capital		**0.038** (0.008)
Time trend		Yes
No observations	60,683	60,683

Note: Weighted average coefficients are reported from regressions estimated within each 4-digit industry in the sample. Coefficients in bold are significant at the 5% level or better. The goodness of fit (R^2) substantially varies across specifications and is in the range 0 – 0.49 as better fit is achieved in specifications with dependent variables calculated by allowing for exporting status.

Table 4 (b): Determinants of company productivity

OLS models of productivity level determinants (s.e. in parentheses)			
	OLS estimates of productivity measure (without regression error)		
EXPORTER	0.012 (0.021)	0.013 (0.023)	0.036 (0.022)
Age		0.017 (0.011)	0.013 (0.011)
Capital		-0.006 (0.005)	**-0.008** (0.004)
First-stage error			**-0.157** (0.013)
Time trend		Yes	Yes
	GLS estimates of productivity measure (without regression error)		
EXPORTER	**0.057** (0.024)	0.005 (0.022)	0.027 (0.022)
Age		**0.217** (0.011)	**0.214** (0.011)
Capital		0.000 (0.005)	-0.001 (0.004)
First-stage error			**-0.148** (0.013)
Time trend		Yes	Yes
	Olley-Pakes 2-step estimates of productivity measure (without regression error)		
EXPORTER	**0.063** (0.028)	0.024 (0.027)	0.025 (0.027)
Age		0.011 (0.014)	0.010 (0.013)
Capital		**0.026** (0.006)	**0.027** (0.006)
First-stage error			**-0.219** (0.022)
Time trend		Yes	Yes
	Olley-Pakes 4-step estimates of productivity measure (without regression error)		
EXPORTER	**0.592** (0.037)	**0.556** (0.037)	**0.537** (0.039)
Age		0.005 (0.018)	0.004 (0.017)
Capital		**0.031** (0.007)	**0.034** (0.007)
First-stage error			**-0.283** (0.028)
Time trend		Yes	Yes
No observations	60,683	60,683	60,683

Note: Weighted average coefficients are reported from regressions estimated within each 4-digit industry in the sample. Coefficients in bold are significant at the 5% level or better. The goodness of fit (R^2) substantially varies across specifications and is in the range 0 – 0.49 as better fit is achieved in specifications with dependent variables calculated by allowing for exporting status.

Table 5: Decomposition of aggregate productivity

Industry (SIC, 2-digit)	Year	Aggregate manufacturing productivity, P	Index of aggregate productivity, P	Index of unweighted mean productivity, $\overline{P}$	Index of covariance term, $\sum_E \Delta s \Delta \omega$	Index of covariance term, $\sum_{NE} \Delta s \Delta \omega$
1	2	3	4	5	6	7
Food and beverages (15)	1994	5.238	1.000	0.688	0.200	0.111
	1996	5.258	1.000	0.676	0.206	0.122
	1998	4.765	0.910	0.696	0.146	0.067
	2000	4.578	0.874	0.684	0.161	0.028
	2002	4.724	0.902	0.678	0.153	0.071
Wearing apparel (18)	1994	4.241	1.000	0.889	0.074	0.037
	1996	4.192	0.988	0.847	0.092	0.049
	1998	4.225	0.996	0.855	0.090	0.051
	2000	4.626	1.091	0.868	0.159	0.064
	2002	4.521	1.066	0.939	0.091	0.035
Pulp and paper (21)	1994	2.337	1.000	1.161	-0.154	-0.007
	1996	2.639	1.129	1.137	-0.012	0.004
	1998	2.584	1.106	1.144	-0.047	0.009
	2000	2.897	1.240	1.194	0.022	0.023
	2002	3.404	1.457	1.254	0.161	0.041
Publishing and printing (22)	1994	4.653	1.000	0.807	0.102	0.090
	1996	4.775	1.026	0.801	0.124	0.101
	1998	4.708	1.012	0.808	0.118	0.085
	2000	4.723	1.015	0.811	0.136	0.068
	2002	4.712	1.013	0.820	0.124	0.068
Chemicals and fuel (23, 24, 25, 26)	1994	4.885	1.000	0.762	0.204	0.033
	1996	4.760	0.974	0.761	0.172	0.042
	1998	4.993	1.022	0.769	0.218	0.035
	2000	5.530	1.132	0.776	0.170	0.185
	2002	5.590	1.144	0.786	0.162	0.197

Basic and fabricated metals (27, 28)	1994	3.626	1.000	0.900	0.063	0.040
	1996	4.003	1.104	0.903	0.168	0.033
	1998	3.574	0.986	0.885	0.069	0.032
	2000	4.362	1.203	0.888	0.278	0.036
	2002	3.912	1.079	0.886	0.164	0.029
Non-electrical machinery (29)	1994	3.924	1.000	0.997	0.023	-0.020
	1996	4.103	1.046	0.976	0.056	0.013
	1998	4.230	1.078	0.992	0.067	0.019
	2000	4.141	1.055	0.984	0.067	0.005
	2002	4.334	1.104	1.010	0.102	-0.008
Electrical machinery (30, 31, 32)	1994	3.290	1.000	0.921	0.084	-0.006
	1996	3.202	0.973	0.948	0.032	-0.006
	1998	3.300	1.003	0.985	0.051	-0.033
	2000	3.398	1.033	1.026	0.014	-0.008
	2002	3.749	1.139	1.070	0.066	0.002
Precision instruments (33)	1994	3.116	1.000	1.054	-0.036	-0.018
	1996	3.323	1.066	1.109	-0.038	-0.005
	1998	3.272	1.050	1.090	-0.042	0.002
	2000	3.441	1.104	1.086	0.024	-0.005
	2002	3.475	1.115	1.110	0.000	0.005
Transportation equipment (34, 35)	1994	4.147	1.000	0.926	0.096	-0.022
	1996	3.768	0.909	0.913	-0.011	0.006
	1998	4.497	1.084	0.889	0.175	0.020
	2000	4.346	1.048	0.908	0.157	-0.017
	2002	4.855	1.171	0.930	0.241	0.000
Furniture and manufacturing n.e.c. (36)	1994	4.326	1.000	0.880	0.099	0.021
	1996	4.295	0.993	0.872	0.089	0.032
	1998	4.206	0.972	0.877	0.066	0.029
	2000	5.080	1.174	0.888	0.086	0.200
	2002	4.308	0.996	0.897	0.065	0.034